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Multiobjective Shape Design in a Ventilation System with a Preference-driven Surrogate-assisted Evolutionary Algorithm

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ABSTRACT

We formulate and solve a real-world shape design optimization problem of an air intake ventilation system in a tractor cabin by using a preference-based surrogate-assisted evolutionary multiobjective optimization algorithm. We are motivated by practical applicability and focus on two main challenges faced by practitioners in industry: 1) meaningful formulation of the optimization problem reflecting the needs of a decision maker and 2) finding a desirable solution based on a decision maker's preferences when solving a problem with computationally expensive function evaluations. For the first challenge, we describe the procedure of modelling a component in the air intake ventilation system with commercial simulation tools. The problem to be solved involves time consuming computational fluid dynamics simulations. Therefore, for the second challenge, we extend a recently proposed Kriging-assisted evolutionary algorithm K-RVEA to incorporate a decision maker's preferences. Our numerical results indicate efficiency in using the computing resources available and the solutions obtained reflect the decision maker's preferences well. Actually, two of the solutions dominate the baseline design (the design provided by the decision maker before the optimization process). The decision maker was satisfied with the results and eventually selected one as the final solution.

KEYWORDS

evolutionary multiobjective optimization; optimal shape design; computational cost; machine learning; metamodel; multiple criteria decision making; Pareto optimality; preference information

1 INTRODUCTION

Industrial optimization problems often have multiple conflicting objectives, which need to be simultaneously optimized. Such problems are known as multiobjective optimization problems (MOPs). For these problems, there typically does not exist a single optimal solution, but a set of optimal solutions can be identified. These solutions which represent different trade-offs between the objectives are known as Pareto optimal (PO) solutions. In MOPs, a decision maker (DM), i.e. an expert in the application domain is usually interested in a single solution or a small set of Pareto optimal solutions to be implemented based on her/his preferences. Thus, it is important to consider the DM's preference information when solving a MOP. Utilizing the DM's preferences has a long history [14, 18, 24] and more recently, evolutionary multiobjective optimization algorithms have also been tailored to incorporate DM's preferences. Some examples of different types of preferences employed in evolutionary methods include reference points [4, 26], pairwise comparison [11], desirable ranges of objective function values [13] and selecting a preferred solution from a small set [6, 13, 23]. For more details about utilizing the DM's preferences in an interactive way, see e.g. [19, 20] and references therein.

Another challenge in solving real-world problems arises from the expensive nature of evaluating objective functions. Real-world optimization problems may, for example, involve time-consuming simulations like computational fluid dynamics (CFD) [7, 12]. In solving such problems, there may be a time limit and one can afford only

a very limited number of function evaluations. Surrogate-assisted optimization algorithms like ParEGO [17] and SMS-EGO [22] have been used in the literature for solving MOPs with expensive function evaluations. For more details about surrogate-assisted multi-objective optimization algorithms, see e.g. surveys [2, 9, 15, 25].

In this article, we focus on solving a computationally expensive shape design MOP and finding a desirable solution based on the DM's preferences. For this, we extend a recently proposed Kriging-assisted reference vector guided evolutionary algorithm (K-RVEA) [8] for incorporating preferences by adapting reference vectors.

In addition to finding a desirable solution, we pay attention to the challenges in the formulation of the optimization problem and connecting different pieces of simulation tools. We use two different simulation tools ANSYS ICEM [3] and ANSYS CFX [27], one for meshing the component and another for CFD evaluations. Both of them are then connected with the extended K-RVEA algorithm. Integrating different simulation tools is common in solving real-world problems, and often requires a substantial amount of time and effort. We demonstrate that identifying objectives reflecting the needs of the DM is far from trivial and can also take several rounds of discussions.

To summarize, in this work, we address the following two major challenges in solving a shape design multiobjective optimization problem of an air intake ventilation system in a tractor cabin:

(1) formulating and modelling the problem to be solved and
(2) finding a desirable solution of this computationally expensive problem based on the preferences of the DM.

As said, the problem to be solved involves time consuming CFD simulations and we formulate three objective functions after three rounds of discussions with the DM. The average computation time for simulation on a computer with Intel Xeon E5-1607 v3 and 32 GB RAM is 30 minutes. The particular component considered in the ventilation system consists of one inlet and four outlets. The flow rates from the outlets play an important role in maintaining a uniform temperature inside the tractor cabin and defrosting the windscreen. Therefore, a balance in the flow rates from different outlets is desired by the DM.

In [10], a simple version of the problem has been considered, where the diameters of the outlets were used as decision variables. A balance in the flow rates in [10] can only be achieved at the expense of increasing the pressure loss. In this study, we develop a more advanced parametric model to get an improved performance.

To alleviate the high computational cost of the three objective functions, we apply the extended K-RVEA algorithm. The algorithm adaptively manages Kriging based surrogates by selecting samples using a criterion called angle penalized distance and uncertainty information from the Kriging models. In [8], the algorithm was found to perform better than state-of-the-art surrogate-asssited multiobjective optimization algorithm on several benchmark MOPs. We extend elements of K-RVEA to incorporate a DM's preferences. One of the main advantages of using K-RVEA over other surrogate-assisted multiobjective optimization algorithms is that it uses reference vectors to guide the , which can be adjusted to handle the DM's preferences. We select samples for updating the surrogates according to the DM's preferences. In this way, we want to utilize the

limited computation resources efficiently by focusing on solutions that are relevant for the DM.

Before starting the optimization, we provide four options to the DM to give one's preferences to guide the search. We also use a recently proposed hypervolume criterion [21] considering the DM's preferences to terminate the solution process. It is important to point out that an appropriate termination criterion is crucial in solving expensive problems. It may happen that after a certain number of function evaluations, there is no improvement in the quality of solutions and running more simulations may not be useful and only wastes computational resources. In [21], the hypervolume criterion is used for comparing different preference based evolutionary algorithms. In this article, we use the criterion for terminating the solution process. We stop the optimization if there is no significant change in the hypervolume after a certain number of function evaluations. After the optimization run is completed, a set of non-dominated solutions obtained corresponding to the preferences is shown and a final solution is selected by the DM.

The rest of the article is organized as follows. In Section 2, we elaborate on formulating the shape optimization problem of a component in the air intake ventilation system by combining different simulation tools. In Section 3, we introduce the methodology of utilizing a DM's preferences in K-RVEA. We present the results of solving the optimization problem in Section 4 followed by conclusions and future research directions in Section 5.

2 FORMULATION OF THE OPTIMIZATION PROBLEM

The air intake serves for air suction and is a part of the tractor cabin's ventilation system. As can be seen in Figure 1, the component considered has four outlets and each outlet leads to a different branch of the ventilation system. In an ideal case, flow rates from these outlets should be the same. However, when designing the component considering manufacturing constraints, there is usually a trade-off between flow rates and pressure loss. The pressure loss ΔP in the system can be expressed as:

$$\Delta P = \Delta P_{friction} + \Delta P_{local},$$

where $\Delta P_{friction}$ is the pressure loss caused by frictional drag, e.g. by the contact of fluid with walls of the component and ΔP_{local} is the local pressure loss caused by whirls and a local geometry shape. Since the diameters and shapes of the outlets are not the same, flow rates from them are inevitably different. In addition, pressure loss increases with flow rates (for details of the relationship between flow rate and pressure loss, see [10]). In an ideal case, the pressure loss should be as low as possible, with all the flow rates from the four different outlets being the same. Obviously, these are conflicting objectives. Yet, for the proper operation of the ventilation system, they both are important. Therefore, the DM is interested in a design where the flow rates from different outlets are the same without too much increase in pressure loss.

As we mentioned in the introduction, problem formulation can be challenging and it is not always straightforward to formulate objective functions and identify decision variables. Generally, this
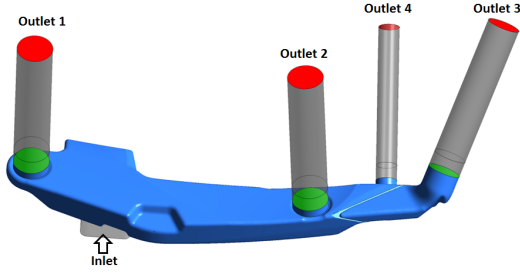
Figure 1: A CFD model of the original component in the air intake ventilation system considered
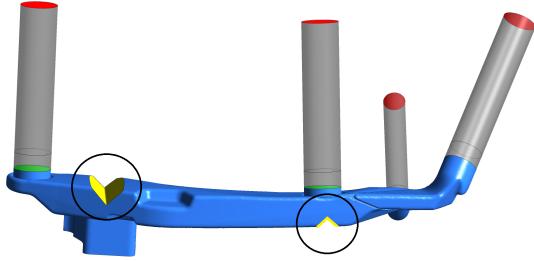

Figure 2: The modified CFD model with added wedges (in circles) at selected locations.

poses a challenge for any real-world engineering problem. It requires identifying the most relevant objectives and their formulation. And ideally, the formulation should be both compatible with the engineering terminology (to make the communication with the DM easier) and to display properties that are suitable for the optimization code (convexity, smoothness, etc.).

In [10], three rounds of discussions with the DM were needed to formulate a simple optimization problem, but the results obtained were not reported to be fully satisfactory. In this article, we reformulate the optimization problem to achieve a better balance in flow rate values from different outlets. Considering manufacturing constraints and the desires of the DM, we have added two wedges in the component as shown in Figure 2. The positions of the wedges were selected based on several CFD simulations prior to optimization. In addition, manufacturing such wedges is easy and does not cause problems in numerical simulations.

The first wedge prevents whirls caused by the inlet flow going directly against a wall and helps in balancing the flow rates between the first and the other outlets. The second wedge helps in directing the flow to the second and the fourth outlet. Both wedges can be described by three variables: angle, height and position. By combining these with the diameters of the outlets, we have a total of 10 decision variables. Note that the decision variables for the baseline design (the design provided by the DM before the optimization process) and the case considered during the optimization are different. There are no wedges in the baseline design and they were introduced in the modelling phase to further improve the design. We used the same objective functions as in [10]:

Table 1: Lower and upper bounds of the decision variables

variable	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}
lower bound	0.5	0.5	0.5	0.5	0	0	10	5	0	60
upper bound	1	1	1	1	1	1	40	20	90	150

f_1 : Minimize variance between flow rates at outlets 1 to 3

: Minimize $var(Q_{1,3})$

f_2 : Minimize static pressure loss of the air intake

: Minimize $P_{inlet} - P_{outlet}$

f_3 : Minimize the difference between the flow rate at outlet 4 and the average of the flow rates at outlets 1 to 3

: Minimize $avg(Q_{1,3}) - Q_4,$

where Q_j represents the flow rate from the jth outlet, P_{inlet} and P_{outlet} are the static pressure values at the inlet and the outlets, respectively, and $avg(Q_{1,3})$ is the average of the flow rates from outlets 1-3. The first and the third objectives ensure that the difference between the flow rates from different outlets is minimized, which is vital for keeping a uniform temperature inside the cabin. The second objective is related to the efficiency of the system, as a high pressure loss equals to requiring a more powerful fan and increases the energy consumption of the ventilation system. Therefore, we minimize the difference between the pressures at the inlet and the outlets as the second objective. The third objective pays special attention to outlet 4. This separation from outlets 1 to 3 is based on practical needs and reflects better the fact that outlet 4 is deemed as a less important one. As it has the smallest diameter compared to the other outlets, maintaining a flow rate from this outlet equivalent to the flow rates from other outlets is difficult. Therefore, we minimize the difference of the flow rates from outlet 4 and the average of the flow rates from outlets 1 to 3 separately.

As far as decision variables are concerned, we have

$$x_i = \frac{D_i}{D_i^{(initial)}} \text{ for } i = 1, \ldots, 4,$$
$$x_i = P_j \text{ for } i = 5, 6 \text{ and } j = 1, 2,$$
$$x_i = H_j \text{ for } i = 7, 8 \text{ and } j = 1, 2,$$
$$x_i = A_j \text{ for } i = 9, 10 \text{ and } j = 1, 2,$$

where D_i is the diameter of the ith outlet and $D_i^{initial}$ is the diameter of the ith outlet in the initial design, provided by the DM. Furthermore, P_j is the relative "left-to-right" position of the wedge peak between two selected points. The height and the angle of the jth wedge are represented by H_j and A_j, respectively, for $j = 1, 2$. The lower and the upper bounds of all decision variables are given in Table 1. The upper bounds of the first four variables were fixed to the initial design values, as increasing the outlet diameters was infeasible due to manufacturing constraints.

In solving the problem, we used two commercial software tools: ANSYS ICEM [3] for meshing the component and ANSYS CFX [27] for CFD simulations and evaluations of the flow rates and pressure loss values. An optimization loop with different simulation
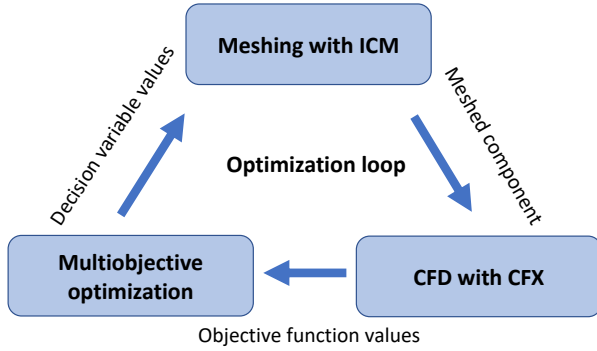
Figure 3: An illustration of the optimization loop with different simulation tools and the optimization algorithm

tools involved and the optimization algorithm (extended K-RVEA) is presented in Figure 3. As can be seen, first the meshing of the component is performed with ICEM and then the meshed component is exported to CFX for numerical simulations. The calculated objective function values are passed to extended K-RVEA for getting the decision variable values. This process is continued until a termination criterion is reached. As mentioned, we used the hypervolume values to stop the solution process to avoid unnecessary time-consuming simulations. The automation of the whole process is accomplished through customized Python codes and modifying pre-made template files.

Because of adding wedges to the parametric model, the average computation time for one function evaluation increased from five minutes to 30 minutes. Because the computation budget was limited, surrogates were needed in the optimization.

3 ADAPTATION OF REFERENCE VECTORS

The K-RVEA algorithm has been designed for problems with three or more computationally expensive objective functions. By approximating expensive objective functions with Kriging models as surrogates, the algorithm reduces computation times. It manages the surrogates with a criterion called angle penalized distance and uncertainties of the Kriging models. For more details about K-RVEA, see [8].

We focus on handling preferences in surrogate-assisted evolutionary multiobjective optimization. This has not received much attention in the literature. It has been shown in [13], that reference vectors can be adjusted according to the DM's preferences. Therefore, we adopt a corresponding strategy and extend the K-RVEA algorithm to find a desirable solution in solving a real-world problem. (Note that in [13], no surrogates were used.) We incorporate the DM's preferences before starting the solution process (and, thus, employ preferences in an a priori fashion [14, 18]). As said, we adapt reference vectors for guiding the search towards a desirable set of approximated Pareto optimal solutions.

We offer four options to the DM to provide one's preferences, which are then used to adjust reference vectors: 1) selecting preferred solution(s) among a set shown, 2) indicating non-preferred solution(s) among a set shown, 3) specifying preferred ranges of objectives and 4) specifying a reference point of desirable objective

function values. Note that it is up to the DM to select an option which best reflects the preferred style of expressing preferences. By giving options, we do not force the DM to using some particular style. Next, we show how the reference vectors are adjusted in the extended K-RVEA based on the preferences.

Let us denote a set of N uniformly generated reference vectors by $V = \left\{ v^i \in R^k | i = 1, \ldots, N \right\}$, where k is the number of objectives. If the DM selects a preferable solution z among a set of alternatives shown, the reference vectors are adjusted as:

$$\bar{v}^i = \frac{r \cdot v^i + (1-r) \cdot v^c}{\left\| r \cdot v^i + (1-r) \cdot v^c \right\|},$$

where $v^c = \frac{z}{\|z\|}$ is considered as a central vector (i.e. the vector to which DM's preferable solution is assigned to) and $r \in (0, 1)$ is the radius which is prefixed and determines how far the reference vectors are from the central vector v^c. In this way, the reference vectors are used only in a small part of the objective space (reflecting the preferences of the DM). If the DM selects several preferred solutions, the same procedure can be utilized for each preferred solution to adjust the reference vectors.

Similarly, if the DM selects a non-preferred solution z, the distance (e.g. Euclidean distance) between the central vector $v^c = \frac{z}{\|z\|}$ and the reference vectors $V = \left\{ v^i \in R^k | i = 1, \ldots, N \right\}$ is measured. Then, the reference vectors closer to the central vector (e.g. based on angle measurements between the reference vectors [5]) are removed. This procedure is repeated for each non-preferred solution if the DM selected more than one.

In case the DM provides preferences in terms of desirable ranges of objective functions $\left[f_i^l, f_i^u \right]$ for $i = 1, \ldots, k$, a k-dimensional hyperbox is created and a set of points is generated within the hyperbox (e.g. with the Latin hypercube sampling). They are then projected to the unit hypersphere to be used as reference vectors. For generating reference vectors when the DM provides a reference point, we use the same procedure as in the case of preferred solutions.

The steps of extended K-RVEA incorporating DM's preferences are listed in Algorithm 1. First, an initial population is generated, e.g. using Latin hypercube sampling, which is then evaluated with the expensive objective functions obtained e.g. by running CFD simulations. The evaluated solutions are added to an archive A. We then ask the DM to provide preferences in any of the four ways detailed above. In case the DM wants to see solutions i.e., trade-offs between the objectives, we show a set of nondominated solutions before we ask the DM to provide preferences. It is important to inform the DM that these solution may not be optimal and she/he uses one's domain knowledge to provide preferences.

Once the DM has provided one's preferences, we generate a uniform set of reference vectors with the same procedure as in [5] and adjust them according to the preferences. We build Kriging models for each objective function using solutions in A. We then use RVEA [5] with Kriging models to obtain samples for updating the surrogates in the next step. In both K-RVEA and RVEA [5], the objective function values are normalized by using objective function values corresponding to extreme reference vectors (with one component equal to 1 and the rest equal to 0). Therefore, extreme

Algorithm 1: Extended K-RVEA: Incorporation of preferences in K-RVEA

Input: N = number of reference vectors
Output: A final solution selected by the DM
Initialization
1. Create an initial population P
2. Initialize the number of function evaluations $FE = 0$ and an empty archive $A = \phi$
3. Evaluate the population P with the original expensive functions and add them to A, update $FE = FE + |P|$
4. Ask the DM for her/his preferences in any of the four ways
5. Generate a uniform set of reference vectors and adjust them according to the DM's preferences
while *Termination criterion is not met* **do**

    5. Train surrogates for each objective function by using individuals in A
    Using RVEA with the surrogates
    6. Run RVEA with Kriging models to find samples for updating the surrogates
    Updating the surrogates
    7. Select samples from the previous step using a selection strategy and denote the set by I
    8. Re-evaluate I with the original expensive functions and update $FE = FE + |I|$, update $A = A \cup I$
    9. Go to step 5

10. Ask the DM for a final solution among the nondominated solutions in A

---

reference vectors should be included in the algorithm. However, as these extreme reference vectors are not generated as per the DM's preferences, we do not include them when updating the surrogates.

To update the surrogates, we first identify solutions generated by RVEA with Kriging models in the objective space for each reference vector (excluding the extreme ones). This is done by measuring the angles between solutions and all reference vectors. For more details about angle measurement, see [5]. Then, we use the similar criterion as in K-RVEA for selecting samples to be used for updating. For each reference vector, we select one sample either with a minimum angle penalized distance (APD) [5] or a maximum uncertainty from the Kriging models. The decision for using APD or uncertainty information is based on the need of diversity which is measured by the change in the number of empty reference vectors (without the extreme reference vector). By empty reference vectors we mean vectors to which no solution has been assigned. If the number of empty reference has increased from the previous update, we use the uncertainty information for updating the surrogates, and otherwise APD is used for selecting the samples. The samples are then evaluated with expensive objective functions and added to the archive A. This procedure (steps 5 to 9) is repeated until a termination criterion is met.

As mentioned in the introduction, we use a hypervolume criterion proposed in [21] considering the DM's preferences to terminate the solution process. We stop if there is no change in the hypervolume for consecutive 10 simulations. In the end, the DM is asked to select one final solution based on her/his preferences among the nondominated solutions in A.

4 RESULTS AND DISCUSSION

In this section, we present the results of solving the design problem of a component in the air intake ventilation system detailed in Section 2 with three objectives and 10 decision variables. Three important parameters in the algorithm are: 1) number of reference vectors $N = 10$, 2) number of samples ($|I|$ in Algorithm 1) to update the surrogates = N, and 3) initial sample size for training the surrogates = 100. The number of reference vectors is kept low as 10 to find a small set of desirable solutions based on the DM's preferences. Due to a small number of reference vectors, we can evaluate all samples after running an evolutionary algorithm (RVEA in this case) with surrogates when updating the surrogates. Therefore, the number of samples in updating the surrogates is equal to the number of reference vectors. Note that we also remove duplicate samples and do not evaluate them with expensive objective functions. We use Latin hypercube sampling for generating the initial population with a size $11n - 1$ as suggested in [16, 17], where n is the number of decision variables. However, nine out of 109 simulations failed and thus we had 100 samples to train the surrogates. It is good to remember that some samples can fail for various reasons when solving real-world problems (e.g., geometry collisions and poor mesh quality in our case). We visualize results to support the DM by using the parallel coordinate plot toolbox [1].

In solving this problem, the DM was not only interested in improving the baseline design but also to explore and learn the tradeoffs between different objectives. Therefore, we did not put constraints on the objective functions as the objective function values of the baseline design. After evaluating the 100 samples with CFD simulations, we asked the DM to provide preferences. He wanted to see solutions first and we showed him a parallel coordinate plot of nondominated solutions of the initial population in the objective space. We present normalized objective function values $f_i = \frac{f_i}{f_{i,\text{baseline}}}$ for $i = 1 \ldots 3$, where $f_{i,\text{baseline}}$ represents the objective function values corresponding to the baseline design provided by the DM.

An illustration of nondominated solutions (normalized) in the objective space is given in Figure 4. As mentioned, we offered four options to the DM to provide his preferences (instead of forcing him to use a particular preference style). Based on his knowledge and expertise, the DM opted for specifying preferred ranges. First, he gave an upper bound for each of the three objective functions. As he was interested in getting as good objective function values as possible, the lower bounds were set as $(0, 0, 0)$. Based on this information, we adjusted the reference vectors, as described earlier. The upper bounds selected by the DM (in green) and the solution corresponding to the baseline design (in red) are shown in Figure 4 besides the nondominated ones shown to the DM.

One can observe in Figure 4 that none of the solutions in the initial sampling is better than the baseline design in the second objective (pressure drop) values. Based on his experience, the DM commented that it might be difficult to get a lower pressure drop value than in the baseline design. Naturally, he was aware of the fact that these solutions are not results of any optimization. One should remember that our focus was to improve the performance of the component in the air intake ventilation system by adding wedges, which were not present in the baseline design.
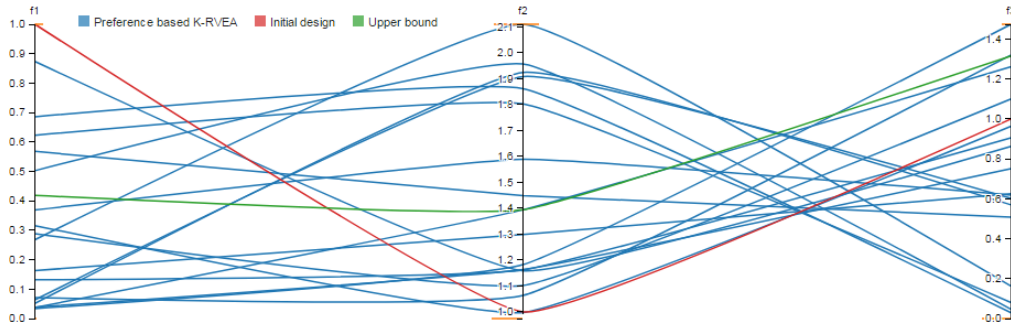
Figure 4: Nondominated solutions from Latin hypercube sampling (in blue) shown to the DM, solution corresponding to baseline design (in red) and upper bounds given by the DM (in green). The figure is available in color online.
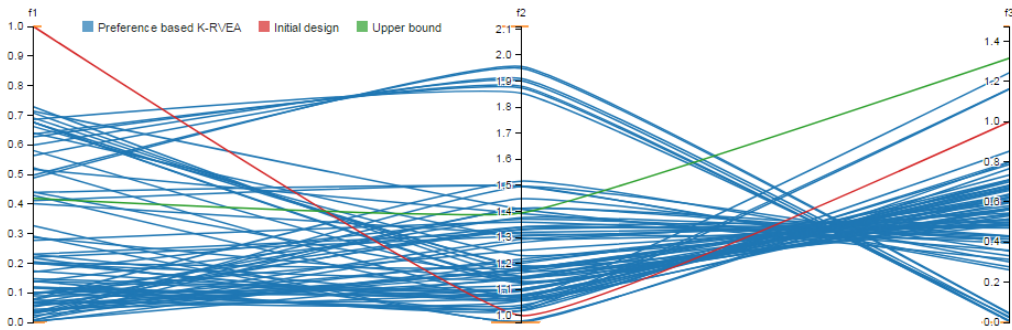

Figure 5: Nondominated solutions from extended ~~preference based~~ K-RVEA (in blue), solution corresponding to baseline design (in red) and upper bounds given by the DM (in green)

The computation time for running one simulation was approximately 30 minutes. Generally, due to the stochastic nature of evolutionary algorithms, it is desirable to run the optimization multiple times to increase the chances of finding as good solutions as possible. To test this, we did three independent runs (each with a different initial population), the maximum we could afford with available computation resources. No significant differences in the outcomes of the three runs were observed, and, in the following, the assembly of the results is considered. Nondominated solutions of the runs in objective (normalized) and decision spaces are presented in Figures 5 and 6, respectively.

A total of 74 nondominated solutions were obtained from all the three runs (with 130 simulations excluding 100 solutions of the initial Latin hypercube sampling). As can be seen in Figure 5, in many solutions, all components lie below the upper bounds given by the DM. In addition, two solutions dominate the baseline design solution. As informed by the DM, getting a lower pressure drop was difficult based on his experience and, therefore, finding two solutions dominating the baseline design shows the value of optimization. Moreover, some of the solutions found a significant improvement in the third objective. These results show the potential of the algorithm to obtain very good solutions in few expensive function evaluations.

For some of the decision variables in Figure 6, many solutions are very close to the bounds of the variables, e.g. diameter of outlet 4,

position of second wedge and angles of both wedges. As mentioned in the introduction, outlet 4 has the smallest diameter (and the hydraulic loss is the highest) compared to the other outlets. Therefore, to achieve an equivalent flow rate from other outlets, the diameter of outlet 4 needs to be at the upper bound. The second wedge is placed at the very end of the allowed range. This is most probably due to the fact that in this position the wedge both helps directing the flow into the second wedge and limits the flow to outlet 3, the one with the highest flow rate in the original design. It is probably a more efficient way than limiting it just by decreasing the diameter of outlet 3. Furthermore, the first wedge tends to have a "sharper" shape (small angle), respecting the inflow direction. The second wedge, on the other hand, is lower and opens wider (bigger angle). By narrowing the passage to outlet 3 it helps in directing the flow into outlet 2 without increasing the hydraulic loss significantly.

Nonetheless, the results show an important aspect. In real-world engineering problems, setting the right variable bounds can be extremely difficult. Wide ranges make the optimization process more time-consuming, yet narrowing down the ranges can exclude the best design from the space. While an experienced DM can help with this problem greatly, sometimes this still remains a challenge.

Finally, we asked the DM to select his most preferred solution among the 74 solutions in the objective space. The DM was positively surprised because two solutions dominated the baseline design and he concentrated on them. He then selected one solution
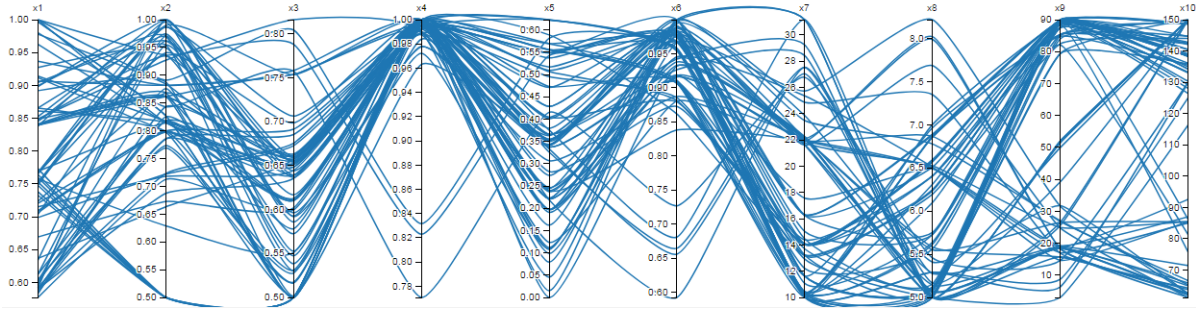
Figure 6: Nondominated solutions from extended ~~preference-based~~ K-RVEA in the decision space
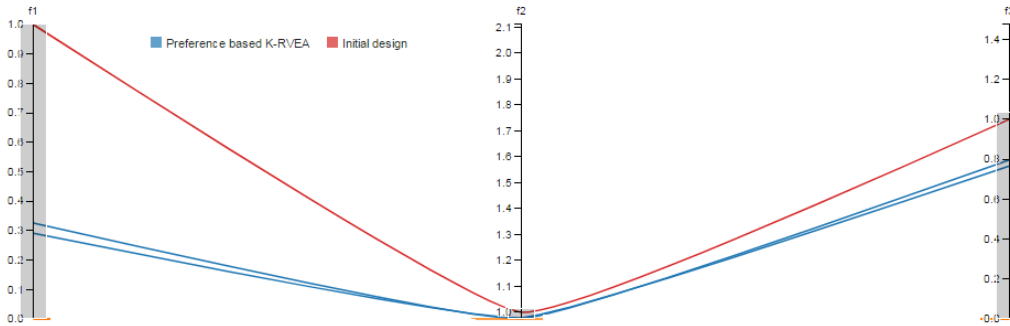

Figure 7: Selection of the final solution by the DM using the parallel coordinate plot

using the parallel coordinate plot tool. A visualization of the two solutions is shown in Figure 7. The final solution has the following (normalized) objective function and decision variable values

$$f_{\text{final}} = [0.29, 0.97, 0.77]$$
$$x_{\text{final}} = [0.85, 0.93, 0.66, 1.0, 0.10, 0.97, 25.71, 8.22, 31.58, 62.49].$$

The streamlines from the CFD simulation of the baseline and the final design are given in Figure 9. In the final design selected by DM, the first wedge helps in guiding the flow between outlet 1 and the other outlets.

In Figure 10, we present for one of the three runs, a plot of the hypervolume criterion (from [21]) with the number of function evaluations, which was used as a stopping criterion. The upper bounds given by the DM were used as the reference point for calculating the hypervolume. As can be seen, after a fixed number of evaluations, there was no improvement in the hypervolume. Therefore, we stopped the optimization after 149 evaluations in this particular run.

We also ran the original K-RVEA without including preferences to show the impact of utilizing the DM's preferences. For a fair comparison, we ran the original K-RVEA for 230 expensive evaluations, as the extended K-RVEA. We could run K-RVEA only once due to the time limit. A parallel coordinate plot of solutions in the objective space obtained from a single run of both algorithms (with and without preferences) is given in Figure 8. As expected, K-RVEA without preferences (in red) tried to cover the whole objective space and none of the solutions is as good as the final solution found by the extended K-RVEA. The latter utilized the computation

resources more efficiently and could find very satisfactory solutions for the DM. Thus, one can say that the limited computing resources available were used more efficiently to meet the DM's needs by incorporating his preference information in the optimization.

5 CONCLUSIONS

In this article, we formulated and solved a real-world computationally expensive multiobjective optimization problem of an air intake ventilation system by including the DM's preferences. The problem involved time-consuming CFD simulations and, therefore, we extended the surrogate-assisted algorithm K-RVEA to reduce the computational cost. Moreover, we offered the DM four possible ways of articulating preference information. We also discussed the importance of formulating and modelling the problem to be solved by using different tools.

The extended K-RVEA algorithm was able to find solutions as per the DM's preferences. Two solutions even dominated the baseline design, which the DM took as a positive surprise. The pressure loss was a bit better than in the baseline design while the other two objectives were improved significantly. Finally, the DM selected one solution based on his preferences as the final solution.

For demonstrating the efficiency of the extended K-RVEA algorithm, we also ran K-RVEA (without any preferences). The results showed that the extended version used the limited computing resources more efficiently and found solutions in that part of the objective space that is desirable for the DM. Thus, the final solution
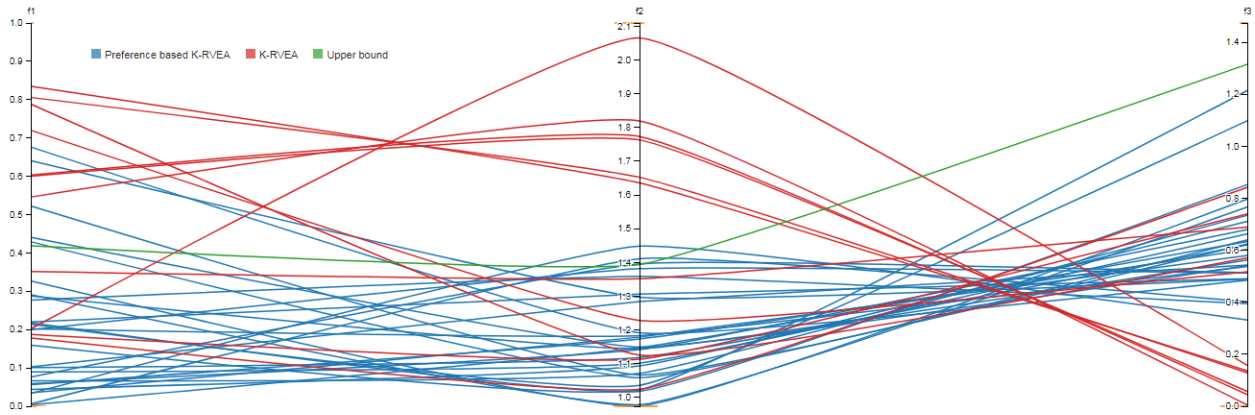
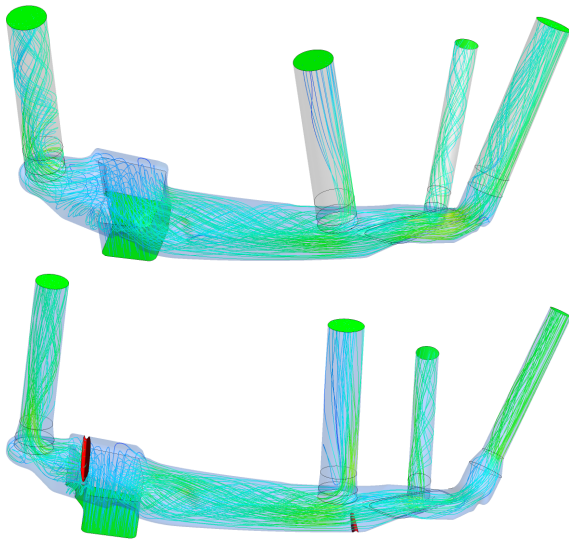Figure 8: Nondominated solutions obtained by extended (in blue) and original K-RVEA (in red)

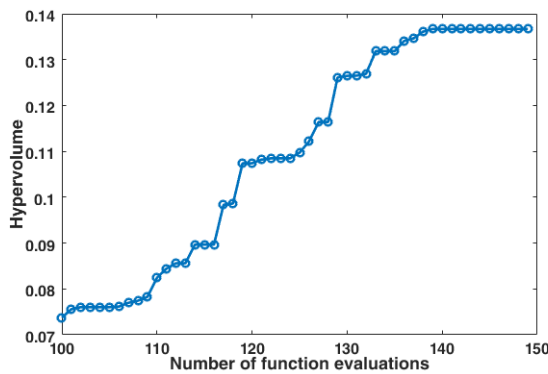Figure 9: A CFD result of the baseline (top) and the final design (bottom) selected by the DM

Figure 10: Hypervolume with the number of function evaluations

found was very satisfactory. On the other hand, the original K-RVEA (without preferences) found solutions that were distributed in the objective space but none of them was comparable to the final solution found with preferences.

In addition to applying the extended K-RVEA in solving the given problem, this article provides insights of solving real-world optimization problems. For instance, dealing with failed simulations, increasing the efficiency of optimization, interacting with a DM, connecting different pieces of simulation tools with the optimizer and visualization are examples of challenges faced by practitioners. By handling these challenges this article provides a distinction in solving benchmark and real-world optimization problems.

We incorporated the DM's preferences before performing the optimization, which is an a priori approach to preference articulation. Developing an interactive version of the algorithm will be our future work. As mentioned, our objective was not to compare different types of preference-handling methods. Instead, we considered a real-world problem with a DM who had substantial knowledge in the application domain, and wanted to offer him freedom in expressing preferences for the optimization. This is an advantage over forcing the DM to provide some fixed type of preferences. Still, we consider different ways of handling preferences in surrogate-assisted optimization as our future research work.

Developing a performance metric reflecting the needs of the DM is another topic for future research. We utilized the parallel coordinate plots to visualize nondominated solutions to the DM, but other visualization tools could also be helpful. Therefore, in the future, we plan to pay attention to other visualization tools to interact with the DM.

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