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A Hybrid Optimization Tool for Active Magnetic Regenerator

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ABSTRACT

Active Magnetic Regenerator (AMR) refrigeration is an innovate technology, which can reduce energy consumption and the depletion of the ozone layer. However, to develop a commercially applicable design of the AMR model is still an issue, because of the difficulty to find a configuration of the AMR parameters, which are suitable for various applications needs. In this work, we focus on the optimization method for finding a common parameters of the AMR model in two application modes: a magnetic refrigeration system and a thermo-magnetic generator. This paper proposes a robust optimisation tool, which ensures the scalability with respect to the number of objectives and allows to easily set up different optimisation experiments. A tool validation is presented. It is expected that this tool can help to make a qualitative jump in the development of AMR refrigeration.

CCS CONCEPTS

• Computing methodologies → Artificial intelligence; Modeling and simulation.

KEYWORDS

real-world application, hybridization, unified optimization

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1 INTRODUCTION

Nowadays, the demand for cooling is increasing, due to the climate change and universal problems. In this context, for reducing the worldwide electricity consumption and direct greenhouse gas emissions, Active Magnetic Regenerator (AMR) refrigeration is a promising technology, which applies the phases of magnetization/demagnetization of solid refrigerants - Magneto Caloric Materials (MCMs) [1].

Despite the promising researches, the AMR development has two principle problems that prevent its commercial production: (i) to simulate physical properties of different MCMs in good qualitative agreement with the available experimental data; (ii) to comprehensively tune many control and design parameters of the AMR model, depending on their effect on its performance. For overcoming these difficulties, related researches apply optimization algorithms to the numerical simulation models of MCMs [6] and AMR [4], [9]. The common challenge of the works aiming at optimizing the AMR performance is to set up many optimization experiments, where different number of objectives and decision variables are required.

For improving optimization process of the AMR design, we develop further the user-friendly tool presented in [6] and integrate an "unified" algorithm in it. The term "unified" is borrowed from [10] for describing the algorithms, which ensure the scalability w.r.t. the number of objectives.We scale the well-known many-objective Non-dominated Sorting Genetic Algorithm III (NSGA-III) [3] down to solve single-objective problems by the hybridization of the solutions of NSGA-III with the solutions of Quantum Particle Swarm Optimization (QPSO) algorithm [11], instead of modifying the NSGA-III structure [10]. It allows NSGA-III to handle very small population size in single-objective cases, which is useful for optimizing time-consuming problems, like the problems of the AMR design. To our best knowledge, this work is the first attempt to apply hybridization to unified optimization.

We contribute by making a step forward the further development of AMR refrigeration for its commercial application and a new insight about hybrid method, which is capable to be employed for constituting scalable algorithms.

2 MATERIALS AND METHODS

2.1 The Simulation Models

The AMR model, provided by Ubiblue Company, operates in two application modes: the Magnetic Refrigeration System (MRS) and the Thermo-Magnetic energy Generator (TMG). In this case, the optimization problems of the AMR model are formulated as the maximization of efficiency and/or power density for the MRS and/or the TMG operating modes for finding optimal control and design parameters of the AMR model in both modes. From an optimization point of view, the AMR model is considered as a continuous, black-box, computationally intensive problem, where the numbers of decision variables and objectives depend on current case study.

Inside the AMR model, for reproducing physical properties of MCMs, we use a method based on the generalize magnetic simulation model provided by the Crismat laboratory [6]. The optimization problems of reproducing physical properties of MCMs are formulated as the minimization of one/several differences between simulated and reference physical properties of MCMs for finding optimal parameters of the magnetic simulation model. From an optimization point of view, these problems can be considered as continuous, computationally intensive, separable or partially separable optimization problems, which can have from one to three objectives.

2.2 Hybrid Unified Optimization Algorithm

Aiming at ensuring the scalability w.r.t. the number of objectives for time-consuming problems, we develop further the idea of unified algorithm [10], by using a hybridization method for scaling down a many-objective algorithm NSGA-III [3] to single-objective optimization. The hybridization is used to overcome difficulties of NSGA-III to solve single-objective problems, which are explained by too small recommended population size of NSGA-III for single objective optimization and an absence of selection pressure [10].

The structure of the proposed algorithm, called QIU-NSA, consists of three main modules: NSGA-III, the modified QPSO and the fusion module (see Figure 1). At generation $t = 0$, the algorithm starts in the fusion module with the definition of the following parameters: (i) the dimension of search space (d); (ii) the dimension of objective space (m); (iii) the vectors of boundaries (lb, ub) for each decision variable; (iv) the threshold of diversity (c_{limit}) and (v) the total number of generations (T_{max}). The diversity coefficient (c_{div}) is set to 0. The termination criterion is defined as the total number of generations. In the fusion module, the initial population $\mathrm{P}^{t=0}$ are created randomly according to the defined boundaries (lb, ub) and evaluated. Then, the following steps are iterated until the termination criterion is satisfied:

(1) `Make Child Population`: The parent population P^t is sent to NSGA-III and QPSO modules in order to produce the new child populations. Each module, NSGA-III and QPSO, creates new set of solutions $\mathrm{Q}^{t+1}_{NSGA-III}$ and Q^{t+1}_{QPSO} according its original rules and returns them into the fusion module.

(2) `Uniform-based Random Selection`: In the fusion module, the populations $\mathrm{Q}^{t+1}_{NSGA-III}$ and Q^{t+1}_{QPSO} are used to select 4 solutions to the next population Q^{t+1} by the following rule:
if uniformly distributed random number $\mathcal{U}(0,1) > 0.5$, the solution of Q^{t+1}_{QPSO} is accepted, otherwise - $\mathrm{Q}^{t+1}_{NSGA-III}$.

(3) `Evaluation of` $\mathbf{Q}^{t+1}$: The obtained population Q^{t+1} is evaluated and is sent back with their evaluated values to the QPSO and NSGA-III modules.

(4) `Selection to the Next Generation`: The solutions for the next parent population P^{t+1} are selected according to the procedure of NSGA-III. QPSO updates the local and global best solutions, according to [11].
At the end of the generation t, the QPSO module returns current global solution g^{t+1} and the NSGA-III module returns the new parent population P^{t+1} to the fusion module.

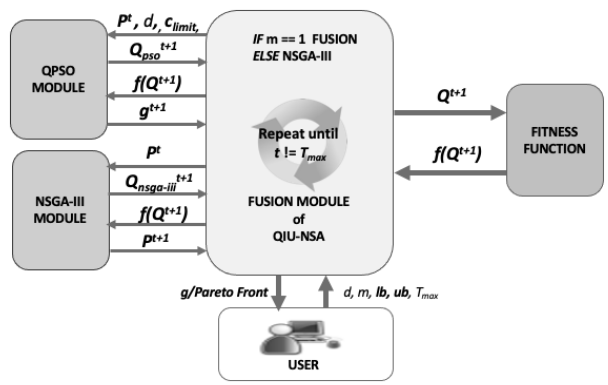


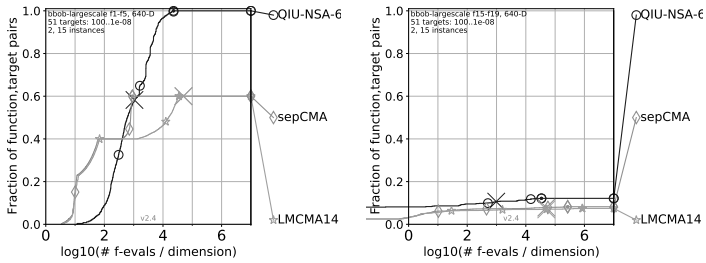
Figure 1: Simplified scheme of the unified algorithm.

To summarise, the hybrid method allows to scale NSGA-III down to solve single-objective problems without any modifications in the NSGA-III structure, which excludes a risk to loss its effectiveness on multi-/many-objective problems.

2.3 Optimization Software Tool

In order to simplify a code-coupling process between each research problem and the proposed unified algorithm, we extend the optimization tool presented in [6], based on the open-source EASEA (EAsy Specification of Evolutionary Algorithms) platform, by implementing QIU-NSA as a template of the EASEA platform. The EASEA provides a compiler for automatically merging a problem description file $*.ez$ (the users' guide is provided in the online documentation[1]), which specifies a scientific research task, with an optimization algorithm template into a CPU parallel C++ code [2].

[1] http://easea.unistra.fr



a) separable b) multi-modal

Figure 2: The ECDF summarized by separable and multi-modal functions on 640-dimensional search space

3 EXPERIMENTS AND RESULTS

3.1 Validation of the Hybrid Unified Algorithm

In order to confirm an ability of QIU-NSA to solve single-objective problems, we benchmark QIU-NSA on the Black-Box Optimization Benchmarking (BBOB) single-objective large-scale test suite [5] provided by the COmparing Continuous Optimizers (COCO) platform[2]. The reported results are based on 15 independent run of 15 instances of each function. Taking into account that the AMR design problems can be large scale, we compare the performance of QIU-NSA on 640-dimensional search space with the reference results of separable CMA-ES (sepSMA) [8] and Limited Memory CMA-ES (LMCMA-ES) [7] provided by COCO platform. Looking at Figure 2, we observe that QIU-NSA demonstrates the best performance on the separable and multi-modal problems with adequate global structure. It solves 100% of separable functions with the highest accuracy (see Figure 2 (a)) that confirms its applicability for separable problems of magnetic model of MCMs. We can conclude that QIU-NSA efficiently scales NSGA-III down on the objective space and shows a good scalability w.r.t. the dimensions of the search space.

3.2 Reproducing Physical Properties of MCMs

The objective of this experiment is to validate an efficiency of QIU-NSA to find a set of the parameters of the magnetic model, which corresponds to the physical properties of the given MCM - *LaFeCoSi* (*LaFeSi*(B)).

3.2.1 Input Parameters and the objective function. The input parameters and their boundary values are presented in Table 1. More details about the method for studying physical properties of MCMs can be found in [6].

Table 1: Input parameters and their boundary values for *LaFeCoSi* alloy

Parameter	H_{field}	K	U_1	U_2	AA	A_{temp}
Value	0.1 - 2.5	0.1 - 2.5	0.1 - 2.5	$= U_1$	-	0.0-2.5

[2]https://github.com/numbbo/coco

The objective function is defined as follows:

$$F = F_{cool} + F_{warm} \tag{1}$$

$$F_{cool} = \mid (\Delta T_{cv_{cool}R}(H_0) - \Delta T_{cv_{cool}}(H_0)) \mid + \mid (\Delta T_{cv_{cool}R}(H_1) - \Delta T_{cv_{cool}}(H_1)) \mid \tag{2}$$

$$F_{warm} = \mid (\Delta T_{cv_{warm}R}(H_0) - \Delta T_{cv_{warm}}(H_0)) \mid + \mid (\Delta T_{cv_{warm}R}(H_1) - \Delta T_{cv_{warm}}(H_1)) \mid \tag{3}$$

where $\Delta T_{cv_{cool}}(H_0)$, $\Delta T_{cv_{warm}}(H_0)$, $\Delta T_{cv_{cool}}(H_1)$ and $\Delta T_{cv_{warm}}(H_1)$ is the the temperature interval width of heat capacity curve peak under different magnetic fields upon cooling and warming process.

3.2.2 Experimental Result. The values of the parameters obtained by the optimization for *LaFeCoSi* are as follows: H_{field} = 1 [T], K = 0.80, U_1= 0.85, A_{temp}=1.00. In Figure 3 we report the temperature dependence of magnetic entropy change (ΔS), which is calculated by using the Maxwells equation from the simulated (theoretical) data with obtained parameters and from the measured data of Crismat. The agreement between the theoretical and measured data is excellent: the Mean Absolute Percentage Error (MAPE) of ΔS is 0.1%.

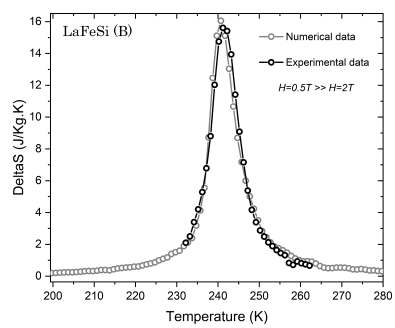


Figure 3: *LaFeCoSi*:The simulated and experimental temperature dependence of magnetic entropy change.

3.3 Optimization of the AMR Design

We apply the proposed tool for developing an innovative architecture of the AMR, which will be efficient for the Magnetic Refrigeration System (MRS) and the Thermo-Magnetic energy Generator (TMG) modes.

3.3.1 Input Parameters. For this experiment, the most important input parameters of the AMR model, which have an impact in the both modes are selected and presented in Table 2 with their boundaries. R_{vol} and f are internal operating conditions that can control the thermodynamic cycles of the AMR, where L are the design parameters.

3.3.2 Experimental Result. Figure 4 depicts the Pareto front of non-dominated solutions, showing in highlighted color values the MRS and TMG operating modes respectively. The Pareto front clearly reveals the conflict between the power densities and efficiency in both modes.

Table 2: The design and control parameters of the dual-mode operating AMR model

Parameter	Boundaries	Unit	Description
L	1-30	[cm]	AMR length along the direction of fluid motion
R_{vol}	0.05-1.5	[-]	Ratio of coolant volume transferred at each half AMR cycle on fluid volume
f	0.1-10	[Hz]	AMR operating frequency

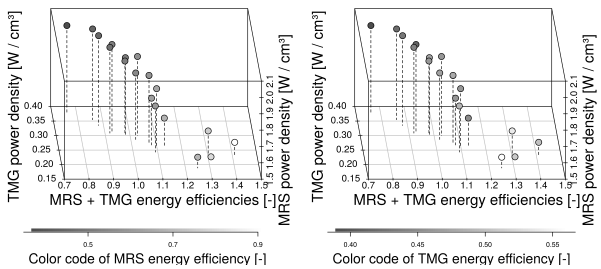


Figure 4: Obtained Pareto Fronts

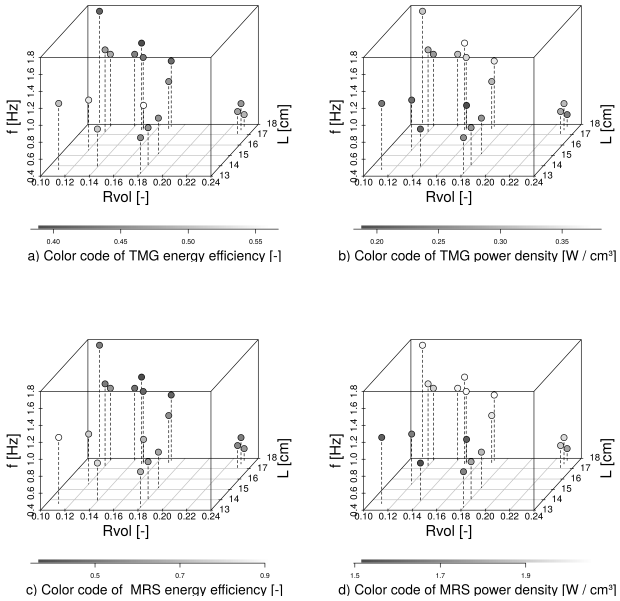


Figure 5: The distribution of Pareto optimal points solutions

A parametric study is conducted to investigate the effects of the variable parameters on the cycle performance through the power density and the efficiency. To make it clear, Figure 5 reports the distribution of Pareto-optimal solutions.

From Figure 5 a) it is seen that the maximum value of the energy efficiency of TMG is 0.56 [−], which is obtained for $L = 17.4$ [cm], whereas the value of $R_{vol} = 0.15$ [−] and $f = 0.69$ [Hz] is small. One can notice that the TMG efficiency range is quite small $0.39 - 0.56$[−]. It can be explained by the fact that the pressure drop is directly proportional to L and thus, a larger value of pressure drop greater penalizes the energy efficiency in the TMG mode. Figure 5 b) shows that the maximum value of the recoverable mechanical power density of the TMG is 0.37 [W/cm^3] , achieved with $f = 1.45$ [Hz], $R_{vol} = 0.15$ [−], and $L = 17.2$ [cm]. Thus, an increase of f leads to increase the mechanical power density and decrease the efficiency. The maximum value of the energy efficiency of the MRS is 0.56 [−] obtained with $L = 13.6$ [cm], $R_{vol} = 0.11$ [−] and $f = 1.18$ [Hz] (see Figure 5 c)). Figure 5 d) shows that the maximum value of the thermal power density of the MRS is $2,05$ [−], which is achieved with the larger value of $L = 17.8$ [cm] and almost the same values of $f = 1.17$ [Hz] and $R_{vol} = 0.11$ [−] as for the the energy efficiency of the MRS.

We can conclude that for all criteria, R_{vol} has less impact than the others. According to Figure 4, there are several solutions, which ensure the balance between efficiency and power density for the both modes. The Pareto fronts has slightly discontinuous shape that be explained by a large number of the rejected solutions, because of their nonexistence in the both modes simultaneously. Thus, an evaluation of the energy conversion system is required by reconsidering some default parameters of the AMR model, e.g., the fluid channel thickness, which was set to optimally match a refrigeration system in this study.

4 CONCLUSION

Optimization of the Active Magnetic Regenerator (AMR) design and reproducing physical properties of Magneto Caloric Materials (MCMs) are the major challenges for the magnetic cooling industry. The proposed tool, thanks to the hybrid method and the EASEA platform, is a robust user-friendly instrument, which allows to easily and efficiently set up different experiments. The functionality of this tool is universal and can be easily adapted to different simulated models. It is validated that thanks to the proposed tool, it is now possible to accelerate the elaboration of a commercially available device, which will correspond to modern ecological and energy-saving requirements.

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