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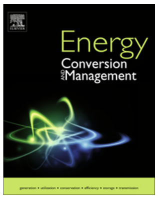

Multi-objective optimization of Stirling engine systems using Front-based Yin-Yang-Pair Optimization

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A B S T R A C T

In this work, we demonstrate the performance of Front-based Yin-Yang-Pair Optimization (F-YYPO) to solve multi-objective problems related to Stirling engine systems. The performance of F-YYPO is compared with that of (i) a recently proposed multi-objective optimization algorithm (Multi-Objective Grey Wolf Optimizer) and (ii) an algorithm popularly employed in literature due to its easy accessibility (MATLAB's inbuilt multi-objective Genetic Algorithm function: *gamultiobj*). We consider three Stirling engine based optimization problems: (i) the solar-dish Stirling engine system which considers objectives of output power, thermal efficiency and rate of entropy generation; (ii) Stirling engine thermal model which considers the associated irreversibility of the cycle with objectives of output power, thermal efficiency and pressure drop; and finally (iii) an experimentally validated polytropic finite speed thermodynamics based Stirling engine model also with objectives of output power and pressure drop. We observe F-YYPO to be significantly more effective as compared to its competitors in solving the problems, while requiring only a fraction of the computational time required by the other algorithms.

1. Introduction

Most engineering optimization problems involve more than one objective which is conflicting in nature [1,2]. This implies that an improvement in one objective is accompanied with deterioration in another objective. While there exist multiple techniques to utilize single objective algorithms to solve multi-objective problems [3], such strategies generally have multiple drawbacks associated with them. One such drawback is that they can provide only a single Pareto solution with a single application of the algorithm. Thus, obtaining a complete Pareto front would require a large number of runs of the single objective algorithm. Stochastic multi-objective optimization algorithms and Constraint Programming [4] on the other hand require only a single execution for obtaining the Pareto front. These algorithms in general are highly flexible techniques which can be employed on complex problems such as combinatorial [5,6] or constrained problems [7]. They have been extensively utilized for a wide range of applications such as large-scale refinery scheduling [8], designing of controllers [9], heat transfer problems [10] and problems related to Stirling systems [11,12]. Most of the stochastic multi-objective algorithms available in literature are based on previously developed single objective optimization algorithms, such as (i) Non-dominated Sorting Genetic Algorithm-II [13] based on Genetic Algorithm [14], (ii) Multi-Objective Differential Evolution [15] and Multi-Objective Differential Evolution with Rank assisted Mutation Operator [16] based on Differential Evolution [17], (iii) Multi-Objective Grey Wolf Optimizer (MOGWO) [18] based on Grey Wolf Optimizer [19], (iv) Multi-Objective Particle Swarm Optimization [20] based on Particle Swarm Optimization [21] and (v) Multi-Objective Artificial Bee Colony [22] based on Artificial Bee Colony [23]. There are many such algorithms which are available in literature [24,25]. All of these multi-objective optimization algorithms may be potentially utilized for the analysis of Stirling engine systems.

A majority of the single and multi-objective stochastic optimization algorithms available in literature are population based techniques. Although these techniques have often been shown to be effective solvers, they generally have the inherent drawback of being complicated and computationally intensive. Yin-Yang-Pair Optimization [26,27] on the other hand is a recently developed single objective optimization algorithm which utilizes two points instead of a population, and was shown to provide highly competitive performance while having a significantly low time complexity. The emphasis on designing a fast optimization algorithm can be observed in the enhancement of YYPO to the multi-objective optimization algorithm Front-based Yin-Yang-Pair Optimization (F-YYPO) [27]. The motivation is to ensure that F-YYPO has the

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Nomenclature

A	area (m^2)
b	distance between wires in the regenerator (m)
C	heat capacitance rate ($W\,K^{-1}$)
c	specific heat ($J\,kg^{-1}\,K^{-1}$)
C_v	specific heat capacity ($J\,mol^{-1}\,K^{-1}$)
d	regenerator wire diameter (m)
D	diameter (m) or number of decision variables
I	direct solar flux intensity ($W\,m^{-2}$) or Intervals of iterations after which the Archive Stage is executed (YYPO)
K_0	heat leak coefficient ($W\,K^{-1}$)
L	length of regenerator (m)
m	mass (kg)
M	proportionality constant (Stirling engine) or number of objectives (optimization)
$M',\ B$	parameters to calculate regenerative losses
n	number of moles
N	rotational speed (rpm) (without subscript) or number (with a subscript)
n'	polytropic exponent
P	power output (W)
p	pressure (Pa)
Pr	Prandtl number
Q	heat (J)
R	the gas constant ($J\,mol^{-1}\,K^{-1}$)
s	stroke length (m)
T	temperature (K)
t	time (s)
$u,\ r$	randomly generated number in the domain $[0,1]$
V	volume or swept volume (m^3)
W	output work (J)
X	coefficient for regenerative losses
y	adjusting coefficient for regenerative losses
$X_1,\ X_2$	coefficients to calculate regenerative losses
λ	ratio of volume during the regenerative processes
σ_0	Stefan-Boltzmann constant ($W\,m^{-2}\,K^{-4}$)
x	solution vector
η	thermal efficiency
h	heat transfer coefficient ($W\,m^{-2}\,K^{-1}$)
α	expansion/contraction factor
δ	search radii
ε	effectiveness and emissivity factor
υ	kinematic viscosity ($m^2\,s^{-1}$)
ρ	density ($kg\,m^3$)
γ	specific heat ratio
τ	temperature ratio

Subscripts

0	ambient
1	inlet
2	outlet
II	second law efficiency
ave	average
c	cold side
cm	compression
cr	cylinder or carnot
d	displacer
$dead$	dead volume
Δp	associated with pressure
ex	expansion
f	friction
g	working fluid
H	heat source
h	hot side
i	decision variable index
L	heat sink
l	lower bound
m	mean
min	minimum
max	maximum
p	piston or pressure
$poly$	polytropic
R	regenerator
r	regenerator gauzes
th	throttling
tot	total
u	upper bound
v	volume

Superscripts

j	decision variable number

ability to provide Pareto fronts in a relatively short computation time without compromising on the quality of the front. The development of F-YYPO is further encouraged by No Free Lunch theorems [28] which state that no single optimization algorithm is capable of providing the best performance on every problem.

Optimization problems relating to Stirling engine systems in literature frequently employ stochastic multi-objective optimization algorithms [29–35]. The Stirling engine is popularly known for its high efficiency (it can theoretically work at Carnot efficiency [36]) and has been widely used for electricity generation from non-conventional heat sources. The externally heated Stirling engine works on a compressible fluid at different temperatures so as to convert heat to mechanical energy, which can in turn be utilized to generate electricity. The modelling of Stirling engine cycles has received considerable attention in literature [37–41]. Entropy, energy and exergy balances at specific elements of the engine were studied for a low temperature Stirling engine at steady state operation using thermodynamic analysis [42]. Additionally, the optimization of the limited heat exchanger's total area was done by considering power generation, thermal efficiency, entropy generation and exergetic efficiency as successive objectives [43]. An investigation was conducted on the effect of various design parameters related to solar collectors on the engine efficiency of the Stirling engine in [44], and an optimization of the power of the engine was performed with the aid of evolutionary algorithms in [45]. A mathematical model for the thermal efficiency of a high temperature solar powered differential dish – Stirling engine with finite – rate heat transfer and finite regeneration processes time was developed and optimized in [46]. The effects associated with regeneration effectiveness and heat capacitance rate of external fluids in heat source/sink at maximum power and efficiency were studied in [47]. The effects associated with irreversibilities of regeneration and heat transfer of heat/sink sources were taken into consideration in [48,49]. A second order model for the Stirling engine was developed using a convective–polytropic heat transfer model in [50]. In addition, various other models of the Stirling engine based on connectionist intelligent modelling [51], finite physical dimensions thermodynamics [52] and finite time thermodynamics [53], predictions of performance of Stirling engines based on least squares support machine

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