#### Energy 76 (2014) 891-898

Contents lists available at ScienceDirect

# Energy

journal homepage: www.elsevier.com/locate/energy

# Weight and power optimization of steam bottoming cycle for offshore oil and gas installations



ScienceDire

Lars O. Nord <sup>a, \*</sup>, Emanuele Martelli <sup>b</sup>, Olav Bolland <sup>a</sup>

<sup>a</sup> Department of Energy and Process Engineering, Norwegian University of Science and Technology, Trondheim, Norway
<sup>b</sup> Department of Energy, Politecnico di Milano, Italy

#### ARTICLE INFO

Article history: Received 22 April 2014 Received in revised form 9 August 2014 Accepted 31 August 2014 Available online 26 September 2014

Keywords: Black-box optimization Multi-objective optimization Genetic algorithm Combined cycle Process simulation Heat recovery

#### ABSTRACT

Offshore oil and gas installations are mostly powered by simple cycle gas turbines. To increase the efficiency, a steam bottoming cycle could be added to the gas turbine. One of the keys to the implementation of combined cycles on offshore oil and gas installations is for the steam cycle to have a low weight-to-power ratio. In this work, a detailed combined cycle model and numerical optimization tools were used to develop designs with minimum weight-to-power ratio. Within the work, singleobjective optimization was first used to determine the solution with minimum weight-to-power ratio, then multi-objective optimization was applied to identify the Pareto frontier of solutions with maximum power and minimum weight. The optimized solution had process variables leading to a lower weight of the heat recovery steam generator while allowing for a larger steam turbine and condenser to achieve a higher steam cycle power output than the reference cycle. For the multi-objective optimization, the designs on the Pareto front with a weight-to-power ratio lower than in the reference cycle showed a high heat recovery steam generator gas-side pressure drop and a low condenser pressure.

© 2014 Elsevier Ltd. All rights reserved.

## 1. Introduction

Today's offshore oil and gas installations are mostly powered by simple cycle GTs (gas turbines). To counter the cost of CO<sub>2</sub> emissions in Norway (taxes and quota), an alternative to a simple cycle configuration could be a combined cycle plant to increase the plant's efficiency and decrease the CO<sub>2</sub> emitted per generated kWh. A steam bottoming cycle, as part of a combined cycle, needs to be simple, with low weight and volume, on an offshore oil and gas installation [1]. On a small scale, a few offshore installations have combined cycles installed [2]. A 2013 increase in the CO<sub>2</sub> tax by the Norwegian parliament may make combined cycles more attractive for the future on the Norwegian continental shelf [3].

One of the keys to the implementation of combined cycles on offshore oil and gas installations is for the steam bottoming cycle to have a low weight-to-power ratio. For the remainder of this paper, the steam bottoming cycle will be referred to as the HRSC (heat recovery steam cycle). The HRSC consists of a HRSG (heat recovery steam generator), a steam turbine, a condenser, various pumps, a water treatment unit, and associated auxiliaries. While the design criteria for maximizing the HRSC power and efficiency are well-known [e.g., see Ref. [4]], those for minimizing the weight-to-power ratio are still unclear. Previous studies of off-shore HRSC installations are based on knowledge-based designs relying on previous experience, literature search, and experts' opinions as exemplified in Ref. [5]. The knowledge-based design methodology is described in Ref. [6].

Direct-search algorithms are widely used in engineering when the objective function is a black-box, e.g., a sequential flowsheet simulation code, or a solver of differential-algebraic equations. Black-box optimizers do not make use of derivative information (they are also called derivative-free methods) as the black-box function may be non-differentiable, discontinuous, not defined in some points of the feasible space, and affected by numerical noise. Well-known examples of such methods are the Simplex method [7], the Pattern Search Algorithm [8], the PSO (particle swarm optimizer) [9], and the several GAs (genetic algorithms) developed since the 1960s. A review and benchmarking of methods can be found in Ref. [10] for unconstrained and bound-constrained problems, and in Ref. [11] for nonlinearly constrained problems. Thanks to their robustness regarding numerical issues, such as numerical noise and discontinuities in the objective function, black-box methods have been successfully applied to several process



<sup>\*</sup> Corresponding author. Department of Energy and Process Engineering, Norwegian University of Science and Technology, Kolbj. Hejes v 1B, 7491 Trondheim, Norway. Tel.: +47 735 93728.

E-mail address: lars.nord@ntnu.no (L.O. Nord).

Nomenclature		Waux	auxiliary power (W)
		Ŵgt	gas turbine gross power (W)
child	child solution vector	W <sub>net,plan</sub>	<sub>t</sub> net plant power (W)
f	objective function	Ŵsc	steam cycle modified power (W)
LHV	lower heating value (kJ/kg)	<b>W</b> <sub>st</sub>	steam turbine gross power (W)
т	mass (kg)	$\Delta p$	pressure drop (bar)
ṁ	mass flow rate (kg/s)	$\Delta p_{ m hrsg}$	gas-side HRSG pressure drop (bar)
$N_f$	number of objective functions	$\Delta T_{\rm cw}$	cooling water temperature difference (K)
N <sub>p</sub>	population size	$\Delta T_{\rm pinch}$	pinch-point temperature difference (K)
N <sub>t</sub>	number of solutions used by the binary tournament	$\eta_{\rm net, plant}$	net plant efficiency (–)
	selection operator	σ	standard deviation
parent	parent solution vector	$\Phi$	parent population
р	population vector	CPSO	constrained particle swarm optimizer
$p_{\rm cond}$	condensing pressure (bar)	GA	genetic algorithm
$p_{steam}$	live steam pressure (bar)	GSS	generating set search
Q	child population	GT	gas turbine
q	vector in the solution space	HRSC	heat recovery steam cycle
rand	random number uniformly distributed between 0 and	HRSG	heat recovery steam generator
	1	MO	multi-objective
ratio	tuning parameter of the crossover operator	NSGA-II	non-dominated sorting genetic algorithm II
<i>RL</i> <sub>gt</sub>	relative gas turbine load $(-)$	OTSG	once-through heat recovery steam generator
Т	temperature (°C)	PSO	particle swarm optimizer
T <sub>steam</sub>	live steam temperature ( °C)	SC	steam cycle
W/P	weight-to-power ratio (kg/kW)	ST	steam turbine
X	solution vector	VGV	variable guide vane

engineering problems since the early 1970s, including steam cycles [12] integrated HRSCs [13], and steam generators [14].

More recently, engineering problems with different possible decision criteria (e.g., minimum weight or cost versus maximum power or efficiency), in which it is not easy to identify a single objective function, are often formulated and tackled as MO (multiobjective) optimization problems by means of evolutionary algorithms [15]. Instead, as for single-objective methods, such as the above mentioned direct-search methods, which return a single solution, evolutionary MO algorithms aim at determining the socalled Pareto frontier, i.e., a set of the most interesting solutions. Indeed, by definition of Pareto-optimality, no feasible solution gives better objective function values than a Pareto-optimal solution for at least one of the objective functions. For example, given two objective functions,  $f_1$  and  $f_2$  (e.g., power and weight), if the solution **x** is Pareto-optimal, no feasible solutions exist with the same value of  $f_1$  and a better objective function value of  $f_2$  and vice versa. Compared to the single solution returned by a single-objective optimizer, knowing the Pareto frontier is very useful in practice because: 1) it indicates not just one but a space of good solutions, allowing the designer to select the solution which best matches the installation constraints; 2) it graphically plots the trade-off between the different objectives (e.g., the gain of power which could be achieved by increasing the weight by a certain amount); and 3) it is possible to derive general criteria by analyzing the features of the Pareto-optimal solutions. As a consequence, MO algorithms have been extensively applied to the design of HRSCs in dual-pressure [16] and other combined cycles [17], Organic Rankine Cycles on offshore platforms [18] and for low grade waste heat [19], and novel energy systems [20].

The aims of this work were to find the minimum weight-topower ratio for a heat recovery steam cycle designed for offshore oil and gas installations, and to determine the trade-off between weight and power. These aims were to be achieved while utilizing a commercial process simulator with detailed process models within an optimization framework. In more detail, a process model of a single pressure level combined cycle was coupled with MATLAB [21] and used as a 'black-box' function by specific optimization algorithms. The process model computed the combined cycle performance and weight for fixed HRSC design variables, which were set by the MATLAB optimizer. Within this framework, firstly PGS-COM, the direct-search algorithm proposed by Martelli et al. in Ref. [22] and described in detail in Ref. [11], was used to determine the solution with minimum weight-to-power ratio; then NSGA-II, the multi-objective optimizer described in Ref. [23], was applied to identify the Pareto frontier of solutions with maximum power and minimum weight.

# 2. Methodology

# 2.1. Process description

The layout for the combined cycle was based on one GT (GE LM2500 + G4), one single-pressure OTSG (once-through heat recovery steam generator), one ST (steam turbine), and a deaerating condenser, as shown in Fig. 1. This setup is explained in more detail in Ref. [5] (layout c). The GT was equipped with dry low emission burners and VGVs (variable guide vanes). The use of VGVs for marine combined cycles is further described in Ref. [24]. Process model assumptions are listed in Table 1. The HRSG designed for an offshore oil and gas installation including design parameter selection is discussed in Ref. [1]. Model validation of the knowledge-based design, which was the starting point for the optimization, was performed in Ref. [5]. For the gas turbine, the exhaust mass flow rate was constant at 90 kg/s for all design cases, whereas the turbine outlet temperature varied slightly (530–534 °C) due to changes in HRSG pressure loss.

### 2.2. Model description

GT PRO (design), GT MASTER (off-design), and PEACE (preliminary engineering and cost estimation) by Thermoflow Inc. were the software used for the combined cycle process modeling, simulations, and weight estimations [25]. Within the Thermoflow Download English Version:

https://daneshyari.com/en/article/8076933

Download Persian Version:

https://daneshyari.com/article/8076933

Daneshyari.com