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Minimum variance control of organic Rankine cycle based waste heat recovery

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ABSTRACT

In this paper, an online self-tuning generalized minimum variance (GMV) controller is proposed for a 100 KW waste heat recovery system with organic Rankine cycle (ORC). The ORC process model is formulated by the controlled autoregressive moving average (CARMA) model whose parameters are identified using the recursive least squares (RLS) algorithm with forgetting factor. The generalized minimum variance algorithm is applied to regulate ORC based waste heat recovery system. The contributions of this work are twofold: (1) the proposed control strategy is formulated under the data-driven framework, which does not need the precise mathematic model; (2) this proposed method is applied to handle tracking set-point variations and process disturbances by improved minimum objective GMV function. The performance of GMV controller is compared with the PID controller. The simulation results show that the proposed strategy can achieve satisfactory set-point tracking and disturbance rejection performance.

1. Introduction

The rapid increasing consumption of energy has resulted in energy shortage and greenhouse effect in all over the world. Efficient energy conservation and environment protection can be achieved by utilizing various low-grade heat in terms of solar power generation [1,2], engine exhaust gases [3], geothermal heat [4], and biological waste heat. Several methods were proposed to recover low grade thermal energy and convert it into higher quality mechanical energy [5]. The viability of implementing recovery energy from industrial processes has been shown by analyzing energy and exergy efficiency [6]. In addition, low grade heat energy was used to drive a silica gel–water adsorption chiller [7], a double stage LiBr–H_2O thermal compressor [8] and a seawater and brackish water reverse osmosis desalination systems [9] respectively.

Organic Rankine cycle (ORC) is a well-known potential candidate in the field of low-grade heat recovery system [10–12]. In such a system, organic working fluids which have larger heat absorption capacities than water can improve heat-exchange efficiency [13]. The ORC systems are characterized by environmentally friendly and high efficiency besides simplicity and availability.

Up till now, some researchers have studied selection of working fluids [13–15] and performances analysis of ORC systems [16–26]. The selection of working fluids was investigated with the help of thermodynamic models, thermal efficiency definition and enthalpy difference analysis [13]. The selection of optimal working fluids was studied based on computer aided molecular design and process optimization techniques [14]. The performances of ORC systems with R113 and R123 working fluids were compared in [15] and it was pointed out that the efficiency of an ORC system depends on working conditions and the thermodynamic properties of the working fluid. The thermodynamic of ORC systems was studied in [16]. It was pointed out that ORC based waste heat recovery process can improve the system performance [17]. The performance analysis and thermo-economic optimization of an ORC system were investigated in [18–21]. Waste heat recovery was investigated using an organic Rankine cycle with two different configurations [22]. The performances of ORCs with different working fluids were analyzed in [23]. The evaluation of isopentane was studied for an ORC system using R-245fa and their mixtures [24]. Based on heat transfer performance analysis, a novel evaporator was designed in [25]. The theoretical analysis of the expander leaving loss varying with the major temperatures in ORC systems was reported in [26].

Modeling for ORC systems has been paid attention by some scholars [27–32]. The mathematical model was built for a scroll expander [27,28]. The physical models of key components in ORC systems were investigated and formulated, the whole ORC system

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Nomenclature

A	areas (m^2)
ρ	density (kg/m^3)
m	mass (kg)
$\dot{m}$	mass flow rate (kg/s)
D	diameter (m)
P	pressure (kPa)
α	heat transfer coefficient W/(m^2 K)
T	temperature (°C)
Cp	heat capacity (J/kg °C)
L	length (m)
h	specific enthalpy (J/kg)
v	velocity (m/s)
μ_T	throttle valve position
N	output power (kW)
w	pump speed (r/min)
$\bar{v}$	specific volume (m^3/kg)
V	volume (m^3)
M	total mass in volume (kg)
W	work per unit time (W)
E	total energy in volume (J)
$\dot{Q}$	heat flow (W)
η	efficiency
T_s	sampling time
$y(k)$	output variables
$u(k)$	input variables
$A(q^{-1})$	the polynomial matrix of output $y(k)$
$B(q^{-1})$	the polynomial matrix of input $u(k)$
$C(q^{-1})$	The polynomial matrix of a random white noise vector $\xi(k)$
$\xi(k)$	a random white noise vector
n	order of polynomial matrix
d	time delay
$\hat{y}(k/\theta)$	estimated outputs
A_i	matrix of state variables
B_i	matrix of input variables
C_i	matrix of disturbances
$\phi^T(k)$	past data vector
$\underset{\frown}{\theta}$	original value of system parameters vector
θ	estimated system parameters vector
k	instant
J	performance index
β	forgetting factor
$K(k)$	estimator gain
$P(k)$	estimation of error variance
$\xi(k)$	unmeasured disturbance
$H(q^{-1})$	weight polynomial of output
$R(q^{-1})$	weight polynomial of set-point
$\lambda(q^{-1})$	weight polynomial of input
$E(q^{-1})$	the solutions of Diophantine equation
$F(q^{-1})$	the solutions of Diophantine equation
$G(q^{-1})$	the solutions of Diophantine equation
n_a	order of $A(q^{-1})$
n_b	order of $B(q^{-1})$
n_c	order of $C(q^{-1})$
n_e	order of $E(q^{-1})$
n_f	order of $F(q^{-1})$
n_g	order of $G(q^{-1})$
n_h	order of $H(q^{-1})$
n_r	order of $R(q^{-1})$
n_λ	order of $\lambda(q^{-1})$

Subscripts

w	wall
f	working fluid
i	inlet or inner
o	outlet or outer
ex	exhaust gas
a	air
exp	expander
con	condenser
eV	evaporator
rec	receiver
p	pump
r	set-point
1	sub-cooled
2	two-phase
3	superheated

models were then built by interconnecting different sub-models in [29–32]. Nevertheless, these models usually need highly complicated computation. Moreover, the existed physical models usually lead to modeling error due to simplification and assumptions in modeling process.

Very few investigations on control of ORC systems have been carried out and reported so far. Three PI control strategies were proposed for ORC systems in [33], the difference among these control laws lies in the employed set-points of the closed-loop control systems: (a) the constant set points of the evaporating temperature and evaporating temperature are determined directly; (b) the variant evaporating temperature is set according to the condensing temperature, the heat source temperature and the heat source flow rate; (c) the optimized working fluid flow rate is determined by the heat source temperature, the condensing temperature and the expander rotational speed. However, the PI control strategies can not necessarily obtain better performance, because the ORC systems are characterized by nonlinearity, uncertainty, multivariable coupling and load disturbances [34,35].

There are stochastic disturbances in ORC systems. For example, the mass flow rate and temperature of waste heat usually fluctuate. In addition, measurement noises are also existed in ORC systems. Hence, it is necessary to investigate control law for ORC systems within stochastic control framework.

This work aims at proposing a controller for a 100 KW ORC based waste heat recovery process. The recursive least squares (RLS) algorithm with forgetting factor is applied to identify the ORC process modelled by a controlled autoregressive moving average (CARMA) model using input/output data of ORC systems. The online self-tuning generalized minimum variance controller is then applied to control multivariable ORC process.

The remainder of the paper is organized as follows: a 100 kW waste heat recovery system with ORC is introduced in Section 2. In Section 3, the physical model of the ORC system is provided, and then the control-oriented model of the waste heat recovery system is identified by using recursive least-square (RLS) algorithm with forgetting factor. A generalized minimum variance controller (GMVC) is then designed to control the waste heat recovery system. Simulation studies are presented to verify the efficiency of the proposed control algorithm in Section 4. Finally, some conclusions are drawn in Section 5.

2. Description of an ORC system

This section aims at introducing an ORC based waste heat recovery system and its control objective. Fig. 1(a) shows the schematic diagram of an ORC based waste heat recovery power plant