PLS-based multi-loop robust H₂ control for improvement of operating efficiency of waste heat energy conversion systems with organic Rankine cycle

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Abstract

Organic Rankine cycle (ORC) is a system suitable for generating electric power by recovering energy from a low-temperature heat source. The system is multivariate, coupled and ill-conditioned. In this paper, a multi-loop robust H_2 control strategy based on the partial least squares (PLS), called PLS- H_2 , is proposed to improve the operating efficiency of a 100kW waste heat recovery process with ORC. Using the PLS framework, the coupled ORC system can be decomposed into multiple single-loop systems in the PLS subspace to facilitate the controller design. The PLS framework compresses the original input and output variables into latent subspaces of the lower dimension, in which the collinearity of the original variables and the noise is eliminated. Taking into account model mismatch and disturbances from the heat source, the robust H_2 controller is designed in each PLS subspace independently. The design is based on minimizing the 2-norm of the transfer function matrix from the exogenous inputs to the controlled outputs. The simulation results demonstrate the effectiveness of the proposed PLS- H_2 and its superiority over PLS-PID control. The proposed control method can achieve better performance than PLS-PID control as the latter has more input efforts by 1,800 times.

Keywords: ill-conditioning; organic Rankine cycle; partial least squares; robust; waste heat energy

1. Introduction

Increasingly severe energy and environmental issues propel people to pay attention to power generation from renewable energy sources and waste heat source. The 2010 World Energy Council survey also indicated energy efficiency and renewable energies are two of the areas requiring highest attention in the world energy agenda [1]. Organic Rankine cycle (ORC) technology has been considered because the ORC system is a waste heat recovery system which can increase energy efficiency and generate renewable power. It can convert the low grade heat into electricity. Moreover, the advantages of ORC are simplicity, favorable operating pressures and low maintenance. In fact, there are abundant sources of waste heat from industrial processes. If this waste heat can be converted into useful electricity, the overall efficiency of an industrial process can be increased. Much research has been conducted to improve the thermodynamic performance of ORCs, such as the selection

of the working fluid [1-4], the heat source type [5, 32], performance analysis and optimization [6-8], the expander selection [9-10], and the choice of cycle architectures [11].

The control strategy also plays a fundamental role on improving the performance of ORC based waste heat energy conversion systems (WHECSs). To ensure viability and efficiency of WHECSs, multivariable model predictive control (MPC) and some other optimal control methods have been applied to ORCs [12-15]. In [12], the generalized predictive control approach was developed for an ORC based on WHECS operated in following the electric load (FEL) mode, and a cost function associated with the stabilization performance was optimized. The power output, throttle pressure, temperatures at the outlets of the evaporator and the condenser were properly controlled then. In [13], a control-oriented method with a physical dynamic model was established and a constrained model predictive control strategy was presented for a WHECS operated in following the waste heat (FWH) mode. The MPC controller showed satisfactory set-point tracking and disturbance rejection ability despite fluctuation of exhaust gas. In [14], the extended self-adaptive prediction control approach to MPC was implemented on ORCs. The cycle efficiency was increased by accurately regulating the superheating and evaporating temperature, especially in the case of unsteady thermal energy source. An online self-tuning generalized minimum variance controller can achieve good performance and deal with stochastic disturbances from measurement noise and exhaust gas in ORCs [15]. However, these methods require online model identification and update at every sampling time, so the difficulty of control design and implementation significantly increases.

Several optimal control methods based on physical models instead of identified models have also been reported [16-18]. An optimal control problem was formulated and its solution was implemented online via dynamic real-time optimization in order to maximize the power produced by an ORC based WHECS with a diesel-electric railcar on board [16]. A multivariable optimal control strategy that combined a linear quadratic regulator and a PI controller was proposed in [17] and was evaluated in a 100kW ORC based WHECS. A mathematical model was established and model reduction was applied so that a simplified control structure could be built. In [18], a linear quadratic integral controller was designed to achieve pressure regulation for

transient waste heat recovery (WHR) in heavy-duty diesel powertrain. In these control methods, the optimization needs to be performed online and the control law needs to be computed and updated at every sampling time, which put a heavy burden on industrial implementation.

The control schemes mentioned above belong to the centralized control. In centralized control framework, its high computational and organizational burden and fragile fault tolerance often make its implementation impractical. In fact, decentralized control schemes, also known as multi-loop control schemes, are preferred in industrial applications. There are fewer parameters to tune, so it is easier for control engineers to implement them. Most importantly, they are tolerant to loop failures. Decentralized PID control algorithms have been applied to ORCs [19-20]. In [19], using a PI controller in each single loop, the expander speed and pump flow rate were manipulated to control the evaporating temperature and the superheating respectively. The superheat was maintained close to the defined value by a gain-scheduled PID controller while a nonlinear feedback controller based on state estimation was designed to allow the evaporating pressure to track the set-point value [20]. However, the control systems mentioned above were based on separate single-input, single-output (SISO) control loop; they did not consider the adverse effect of system-wide interactions.

The ORC based WHECSs are characterized by ill-conditioning, severe coupling, and uncertainty. Loop pairing and decoupling are essential for multi-loop control design for ORCs. Traditional decoupling methods are invalid for ill-conditioned plants. Kaspar and Ray[21] first proposed the control system design in the latent subspace under the partial least squares (PLS) framework. The benefit of the PLS control structure is that the interaction among loops can be decoupled to a certain extent by decomposing the multi-input multi-output (MIMO) process into several independent SISO systems in PLS latent spaces. Therefore, loop pairing is avoided, and the ill-conditioned or non-square process can be easily handled. This PLS control framework has been further developed by many researchers [22-25]. In addition, a great challenge for ORC based WHECSs is the drastic and frequent disturbances from heat sources. The waste heat sources from industrial processes or engine exhaust gases always experience large fluctuations of flow rate and temperature over time.

1 These disturbances and other imperfections in the models used in real ORCs have
2 significant impacts on the system steady-state operation, so it renders the control task
3 difficult.

4
5 For practical consideration of the operating ORC, the system uncertainty must be
6 taken into consideration in the controller design procedure to promise a higher control
7 performance. However, in the former studies, the robustness of ORCs in the presence
8 of system uncertainties and disturbances from heat sources and measurement noises
9 has not been considered. In this paper, robust H_2 control is adopted in the PLS
10 framework to improve the robustness of ORCs. A dynamic PLS control framework of
11 the ORC based WHECSs is presented. It can compress the original input and output
12 variables into latent subspaces of the lower dimension, in which the collinearity of the
13 original variables and the noise is eliminated. Taking into account model mismatch
14 and disturbances from the heat source, the robust H_2 controller is designed. It is based
15 on minimizing the 2-norm of the transfer function matrix from the exogenous inputs
16 to the controlled outputs.

17 18 **2. System description**

19 An ORC based WHECS operated in the FEL mode and its control tasks are
20 presented in this section. Fig.1 (a) illustrates the basic ORC and the corresponding
21 heat transfer process in the T - s diagram is shown in Fig. 1(b). As observed in Fig.1(a),
22 the main components of the ORC system include an evaporator, an air cooled
23 condenser, a valve, an expander, and a working fluid pump. The working fluid
24 operates in a sealed, closed-loop cycle. The heat source, such as exhaust gas of power
25 plants or any other fluid carrying source heat, is sent to the evaporator and transferred
26 to the working fluid. The working fluid R245fa in the sub-cooled liquid phase is
27 heated until it becomes superheated vapor. Then the vapor with high pressure and
28 temperature is sent to the expander and then it becomes the vapor with lower pressure
29 and temperature. As a result, the electric power is generated. The lower pressure and
30 temperature superheated vapor is condensed into liquid state when passing through an
31 air cooling condenser. Finally, the working fluid pump pushes the fluid into the
32 evaporator, and then a new cycle begins.

33
34 In WHECS operated in an FEL mode shown in Fig. 1, the expander and the

generator are linked with the same shaft, and the generator is connected to the power grid without a power converter interface. The rotating speed of the generator (or the expander) is determined by the grid frequency and the number of poles of the stator winding. The electric power output needs to follow the electric load demand from the power grid. A control system is necessary to keep the electric power output in balance with the electrical load demand while maintaining other important process variables, such as pressure and temperature within desired ranges. The control tasks of the WHECSs under this kind of operating mode can be summarized as follows:

- (1) The produced electric power from the generator needs to follow the variations of the electric demand.
- (2) The evaporating pressure must be kept at a desired value.
- (3) The temperature at the outlet of the evaporator should be well controlled to avoid poor performance because of excessive critical temperature of the working fluid, and to prevent wet vapor from entering the turbine when the temperature is too low.
- (4) The regulation of the temperature at the outlet of the condenser is also necessary to ensure a safe and highly efficient operation mode of the whole system. When the sub-cooling is in the range of $0.5-0.6^{\circ}\text{C}$, the system achieves its best performance[26].

As a consequence, the above requirements are fulfilled by controlling the following CVs (controlled variables): the power output of the turbine expander N (KW), the evaporation pressure P_e (MPa), the temperature at the outlet of the evaporator T_{sh} ($^{\circ}\text{C}$) and the temperature at the outlet of the condenser T_{ch} ($^{\circ}\text{C}$). Several MVs (manipulated variables) are chosen, including the throttle valve position μ_T (%), the pump speed w (rad/min), the mass flow rate of exhaust gas $\dot{m}_e$ (kg/s) and the mass flow rate of cold air $\dot{m}_c$ (kg/s). Because of the multivariable coupling characteristic of ORC systems, it is necessary to pair the MVs and the corresponding CVs according to prior knowledge of the ORC model. In this paper, the loop pairing can be avoided since the PLS control framework is used. The control framework will be developed in the next section.

3. Dynamic PLS control framework

The investigated ORC model in this paper comes from the reference [17] and the detailed modeling process is beyond the scope of this paper. The linearized ORC system can be represented by the Eq.(27) in [17] as follows:

$$\begin{aligned}\dot{\mathbf{x}} &= \mathbf{Ax} + \mathbf{Bu} \\ \mathbf{y} &= \mathbf{Cx} + \mathbf{Du}\end{aligned}\tag{1}$$

The ORC system was described as ill-conditioned and coupled in [17]. This interaction could lead to oscillation and even instability, which cause the designed controllers to be very sensitive to system uncertainty. Another problem of the ORC system is the issue of model uncertainty. The model representation of a system often involves simplified assumptions. That is, control systems are designed using much simplified models. They may not work in a real plant. To solve the above issues, the PLS control framework without loop pairing is proposed in this paper to break down couplings among variables in ORCs. The multi-loop robust control strategy for the ORC system under the PLS framework is shown in Fig.2. In this framework, the controlled and manipulated variables can be transformed into a smaller informative set via a set of linear functions ($\mathbf{Q}$ and $\mathbf{P}$), which models the combinational relationships between the controlled variables and latent controlled variables, and between the manipulated variables and latent manipulated variables, respectively. The matrices, such as diagonal scaling matrices ($\mathbf{W}_x$ and $\mathbf{W}_y$) and loading matrices ($\mathbf{P}$ and $\mathbf{Q}$), are introduced using the PLS algorithm. $G_{cr}, (0 < r \leq R)$ is the transfer function of the controller in the PLS latent space, which will be discussed in Section 4.

3.1 Partial least squares

PLS was developed by Wold [27] for model building. It is a dimensionality reduction technique for maximizing the covariance between the input matrix $\mathbf{X}$ and the output matrix $\mathbf{Y}$ for each component in the reduced space. The advantage of PLS over other linear regressions is that the outer model projects the original data into latent spaces, by which the orthogonality of the score vectors is achieved. PLS computes loading and score vectors that are correlated with the predicted block while

describing a large amount of the variation in the predictor block.

PLS requires an input (predictor) variable matrix $\mathbf{X} = (x_{ij})_{n \times m}$ and an output (predicted) variable matrix $\mathbf{Y} = (y_{ij})_{n \times p}$, where n denotes the total number of observations in the training set; m is the number of predictor variables; (in this study, $m = 4$, and the predictor variables include the throttle valve position μ_t , the pump speed w , the mass flow rate of exhaust gas $\dot{m}_e$ and the mass flow rate of cold air $\dot{m}_c$.) p is the number of predicted variables ($p = 4$, and the predicted variables include the power output of the turbine expander N (kW), the evaporation pressure P_e (MPa), the temperature at the outlet of the evaporator T_{sh} ($^{\circ}\text{C}$) and the temperature at the outlet of the condenser T_{ch} ($^{\circ}\text{C}$)). Both $\mathbf{X}$ and $\mathbf{Y}$ are mean-centered and scaled by the standard deviation. In standard PLS, the scaled and mean-centered matrices $\mathbf{X}$ and $\mathbf{Y}$ are decomposed as a sum of series of rank-one component matrices. These decompositions yield outer relations,

$$\begin{aligned}\mathbf{X} &= \mathbf{t}_1 \mathbf{p}_1^T + \mathbf{t}_2 \mathbf{p}_2^T + \cdots + \mathbf{t}_R \mathbf{p}_R^T + \mathbf{E} = \mathbf{T} \mathbf{P}^T + \mathbf{E} \\ \mathbf{Y} &= \mathbf{v}_1 \mathbf{q}_1^T + \mathbf{v}_2 \mathbf{q}_2^T + \cdots + \mathbf{v}_R \mathbf{q}_R^T + \mathbf{F} = \mathbf{V} \mathbf{Q}^T + \mathbf{F}\end{aligned}\quad (2)$$

where $\mathbf{t}_r$ and $\mathbf{v}_r$ are the r th ($0 < r \leq R$) orthogonal latent variable vectors, and $\mathbf{p}_r$ and $\mathbf{q}_r$ are r th latent loading vectors. $\mathbf{T}$ and $\mathbf{V}$ are the corresponding score matrices, and $\mathbf{P}$ and $\mathbf{Q}$ are the loading matrices. $\mathbf{E}$ and $\mathbf{F}$ are the residual matrices of $\mathbf{X}$ and $\mathbf{Y}$. R is the number of the latent variables which is determined by the cross validation method in this paper.

The relationship between $\mathbf{X}$ and $\mathbf{Y}$ is constructed by the inner relation between $\mathbf{v}_r$ and $\mathbf{t}_r$, which can be described by

$$\hat{\mathbf{v}}_r = b_r \mathbf{t}_r \quad (3)$$

where $b_r = \frac{\mathbf{v}_r^T \mathbf{t}_r}{\mathbf{t}_r^T \mathbf{t}_r}$ is the linear regression coefficient. Thus, the total information explained in matrix $\mathbf{Y}$ can be expressed as

$$\hat{\mathbf{Y}} = \sum_{r=1}^R b_r \mathbf{t}_r \mathbf{q}_r^T = \mathbf{TBQ}^T \quad (4)$$

Matrices $\mathbf{X}$ and $\mathbf{Y}$ are related through their scores by the inner relationship $\hat{\mathbf{v}}_r = b_r \mathbf{t}_r$. The coefficients $b_r, r=1, 2, \dots, R$, are the elements of the diagonal matrix $\mathbf{B}$. They are determined by maximizing the correlation between $\mathbf{X}$ and $\mathbf{Y}$. The detailed description of the PLS algorithm can be found in [28].

3.2 Dynamic PLS control framework

Dynamic models are required for the controller design while the standard PLS only deals with static rather than dynamic relationships. Attempts were made to incorporate dynamics. Kaspar and Ray [21] developed a dynamic PLS modeling by imposing the dynamic filter on the input data before using the standard PLS procedure. The dynamic transformation was represented by the dynamic filter as $\mathbf{H}(\cdot)$. Kaspar and Ray [31] also have verified that the dynamic transformation become part of the inner relation of the final PLS model. Thus Kaspar and Ray's method is chosen in our work to avoid the dimension expansion, leading to a simple adaption of the PLS model for control system design. The dynamic PLS inner model $\mathbf{BH}$ is a diagonal matrix and it can be denoted as

$$\mathbf{BH} = \begin{bmatrix} G_{p1}(s) & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & G_{pR}(s) \end{bmatrix} \quad (5)$$

A standard least squares method is used to optimize the dynamic filter parameters.

After the PLS algorithm is performed, the ORC process is pre-multiplied by the matrix $\mathbf{W}_x \mathbf{P}$ and post-multiplied by the matrix $\mathbf{Q}^+ \mathbf{W}_y^{-1}$ as shown in Fig.2. $\mathbf{Q}^+$ is the appropriate Moore-Penrose inverse of $\mathbf{Q}$. It can be seen in Fig.2 that the input $\mathbf{X}$ and the output $\mathbf{Y}$ in the original physical space are projected as $\mathbf{t}_r$ and $\mathbf{v}_r$ ($r=1, \dots, R$) in the latent space. Due to the orthogonality of the score vector pairs $\mathbf{t}_r$

and $\mathbf{v}_r$, the resulting transformed inputs $\mathbf{T}$ and outputs $\mathbf{V}$ are completely decoupled. Within the PLS control framework, loop pairing is avoided, ill-conditioning is eliminated in the PLS decoupling design, and the MIMO ORC system is decomposed into a series of univariate subsystems. Thus, each univariate subsystem can be separately considered and a conventional SISO controller G_{cr} can be directly applied to each PLS latent space (Fig. 2) to achieve the desired performance. Unlike the conventional decoupling design, PLS decoupling is still centralized, but a control design uses all the process input and output measurements simultaneously to determine the values of all the input variables.

4. Multi-loop robust controller design within PLS framework for ORC system

As stated in the previous section, the MIMO ORC process has been converted into several independent SISO loops under the PLS control framework. One of the single control loops in the PLS subspace is shown with the dash-dotted box in Fig. 2. The complex and interactive nature of multivariable control systems has been eliminated. Most of the automatic tuning methods intended for SISO processes can be applied. However, because of occlusions, malicious tampering, or sensor failures, the weakness of identified PLS models with respect to grossly corrupted models often results in inaccuracy. In this section, the robust H_2 controller is designed in each single loop to cope with system uncertainties and disturbances from waste heat sources and measurement noises [33].

The standard mixed sensitivity H_2 problem is to find a stabilizing controller that minimizes the H_2 norm in Eq.(6) of the closed-loop transfer function,

$$\|\mathbf{T}_{zw}\|_2 = \left\| \begin{bmatrix} \mathbf{W}_1 \mathbf{S} \\ \mathbf{W}_2 \mathbf{G}_c \mathbf{S} \\ \mathbf{W}_3 \mathbf{T} \end{bmatrix} \right\|_2 \quad (6)$$

where $\mathbf{W}_1$, $\mathbf{W}_2$ and $\mathbf{W}_3$ are weighting functions. The sensitivity function is

$\mathbf{S} = (\mathbf{I} + \mathbf{G}_p^* \mathbf{G}_c)^{-1}$ and the complementary sensitivity function is

$\mathbf{T} = \mathbf{G}_p^* \mathbf{G}_c (\mathbf{I} + \mathbf{G}_p^* \mathbf{G}_c)^{-1}$. Here, $\mathbf{G}_p^*$ is the nominal model of the compensated ORC

1 plant, $\mathbf{Q}^+ \mathbf{W}_y^{-1} \mathbf{G} \mathbf{W}_x \mathbf{P}$ where $\mathbf{G}$ is the transfer function of the ORC process model.

2 In the previous section, the compensated plant model can be approximated by the PLS
3 inner model, $\mathbf{B}\mathbf{H}$. Thus, Eq.(6) can be transformed to Eq.(7),

$$\|\mathbf{T}_{zw}\|_2 = \left\| \begin{bmatrix} \mathbf{W}_1 \mathbf{S} \\ \mathbf{W}_2 \mathbf{G}_c \mathbf{S} \\ \mathbf{W}_3 \mathbf{T} \end{bmatrix} \right\|_2 = \left\| \begin{bmatrix} \mathbf{W}_1 (\mathbf{I} + \mathbf{B}\mathbf{H}\mathbf{G}_c)^{-1} \\ \mathbf{W}_2 \mathbf{G}_c (\mathbf{I} + \mathbf{B}\mathbf{H}\mathbf{G}_c)^{-1} \\ \mathbf{W}_3 \mathbf{B}\mathbf{H}\mathbf{G}_c (\mathbf{I} + \mathbf{B}\mathbf{H}\mathbf{G}_c)^{-1} \end{bmatrix} \right\|_2 \quad (7)$$

6
7 In Eq.(5), the diagonal element $G_{pr}(s)$ in the matrix of $\mathbf{B}\mathbf{H}$ serves as the
8 model transfer function in the r th latent subspace. Thus, in Eq.(7), all the matrices are
9 diagonal matrices and the MIMO control design has been separated into several
10 independent control loop designs in the latent subspace with the PLS compensation
11 structure. The MIMO H_2 control structure can be separately designed to find a
12 stabilized controller that minimizes the H_2 norm of Eq.(8) for each loop in the latent
13 subspace,

$$\|T_{wz}\|_2 = \left\| \begin{bmatrix} \frac{W_{r1}}{(1 + G_{pr} G_{cr})} \\ \frac{W_{r2} G_{cr}}{(1 + G_{pr} G_{cr})} \\ \frac{W_{r3} G_{pr} G_{cr}}{(1 + G_{pr} G_{cr})} \end{bmatrix} \right\|_2, \text{ for all } r \in (0, R] \quad (8)$$

16
17 To explain the robust controller design, one of the single control loops in the PLS
18 subspace shown with the dash-dotted box in Fig. 2 is discussed. The standard
19 configuration of the closed loop system with weighted functions in one PLS subspace
20 is illustrated in Fig. 3, where exogenous inputs and control inputs are shown on the
21 left-hand side as w_r and t_r , the output signals related to the performance of the
22 control system and the measured outputs are shown on the right as z and v_r .

23
24 According to Fig.3, the input-output relations can be written as

$$\begin{aligned}
z_1 &= W_{r1}(s)w_r - W_{r1}(s)G_{pr}(s)t_r \\
z_2 &= W_{r2}(s)t_r \\
z_3 &= W_{r3}(s)G_{pr}(s)t_r \\
v_r &= w_r - G_{pr}(s)t_r
\end{aligned} \tag{9}$$

The above equations can be rewritten in the packed-matrix form

$$\begin{bmatrix} \mathbf{z}_r \\ v_r \end{bmatrix} = \begin{bmatrix} W_{r1} & -W_{r1}G_{pr} \\ 0 & W_{r2} \\ 0 & W_{r3}G_{pr} \\ 1 & -G_{pr} \end{bmatrix} \begin{bmatrix} w_r \\ t_r \end{bmatrix} = \begin{bmatrix} \mathbf{P}_{r11} & \mathbf{P}_{r12} \\ \mathbf{P}_{r21} & \mathbf{P}_{r22} \end{bmatrix} \begin{bmatrix} w_r \\ t_r \end{bmatrix} \tag{10}$$

where $\mathbf{P}_r = \begin{bmatrix} \mathbf{P}_{r11} & \mathbf{P}_{r12} \\ \mathbf{P}_{r21} & \mathbf{P}_{r22} \end{bmatrix}$ is the generalized plant model. Thus, the closed loop transfer function from the command value w_r to the output $\mathbf{z}$ is given

$$\begin{aligned}
T_{zw} &= P_{r11}(s) + P_{r12}(s)[I - G_{cr}(s)P_{r22}(s)]^{-1}G_{cr}(s)P_{r21}(s) \\
&= \begin{bmatrix} W_{r1}S_r \\ W_{r2}G_{cr}S_r \\ W_{r3}T_r \end{bmatrix}
\end{aligned} \tag{11}$$

where S_r and T_r are the sensitivity function and the complementary sensitivity function in the r th PLS latent space. They can be expressed by the following equations

$$S_r(s) = \frac{1}{1 + G_{cr}(s)G_{pr}(s)} \tag{12}$$

$$T_r(s) = \frac{G_{pr}(s)G_{cr}(s)}{1 + G_{pr}(s)G_{cr}(s)} \tag{13}$$

Therefore, the MIMO controller design problem finds admissible G_{cr}

($0 < r \leq R$), which minimizes $\|T_{zw}\|_2$ of each closed loop transfer function in the PLS subspaces. The control design can be formulated as:

$$\min_{G_{cr}} \|T_{wz}\|_2, \text{ for all } r \in (0, R] \quad (14)$$

The robust H_2 control design procedures based on the PLS multi-loops can be summarized in the following steps:

Step 1. Collect the data of input variables $\mathbf{X}$ and output variables $\mathbf{Y}$. Scale $\mathbf{X}$ and $\mathbf{Y}$ to be zero mean and unit variance. Obtain scaling matrices $\mathbf{W}_x$ and $\mathbf{W}_y$.

Step 2. Perform the PLS algorithm and determine the parameters of the filter of $\mathbf{H}(s)$. Then the loading matrices, $\mathbf{P}$ and $\mathbf{Q}$, as well as the regression coefficients matrix $\mathbf{B}$ are obtained.

Step 3. Apply the loading matrices $\mathbf{P}$ and $\mathbf{Q}$ with the scaling matrices $\mathbf{W}_x$ and $\mathbf{W}_y$ as the pre-compensator and the post-compensator in Fig. 2 so that the control system can be designed in the PLS latent space. The PLS model is built offline for one time and then the model can be directly used for controller design.

Step 4. Design multi-loop robust H_2 controllers based on the dynamic PLS framework.

Because of the ill-conditioned WHECS, the system is decoupled into several single control loops in the latent space of PLS. The difficulty of loop pairing of the controlled and manipulated variables for conventional decoupling control design is avoided. Moreover, without the design of centralized control for the multivariable WHECS system, the controllers can be separately designed for each control loop in the latent space. Therefore, the design of the controllers is no longer a tedious and time-consuming task.

5. Simulation studies

In this section, the performance of the proposed control strategy based on the ORC process model in the reference [17] is tested. The nominal operating condition is given as: $N=100kW$, $P_e=2MPa$, $T_{sh}=137.6^\circ C$, $T_{ch}=31.7^\circ C$, $\mu_T=88\%$, $w_p=2850r/min$, $\dot{m}_e=7.44kg/s$ and $\dot{m}_c=2.6kg/s$. According to the steady-state gain matrix of the ORC process, RGA can be given as:

$$\lambda = \begin{bmatrix} 0.33 & 25.76 & 1.91 & -2 \times 10^{-3} \\ -1.58 \times 10^4 & -7.27 \times 10^5 & -9.18 \times 10^4 & 60.56 \\ 5.34 \times 10^4 & -1.94 \times 10^6 & 3.1 \times 10^6 & 173.64 \\ 0.41 & -21.48 & 2.36 & 0.001 \end{bmatrix}$$

and the condition number for the process currently under investigation is 3.86×10^7 , which is quite large. This multivariable process is proved to be ill-conditioned and difficult to control, reflecting a slow, oscillatory, coupled response with significant overshoot. A coupling and ill-conditioned system is selected for the case studies.

Four pseudorandom signals are applied to excite the ORC system, and a total of 200 sets of data are collected. Measurement noises with a signal-to-noise ratio of 10 are added to both outputs. The input data and the response data are scaled for PLS modeling. The explained variances captured by each PLS latent variable are listed in Table 1. As seen in Table 1, three latent variables explain over 98% of the variance of the data. Thus, three control loops ($R=3$) in the PLS space are selected for the controller design. The dynamic PLS model is obtained:

$$\mathbf{BH} = \begin{bmatrix} \frac{-0.1884s + 0.02248}{s^2 + 0.03202s + 0.0001289} & 0 & 0 \\ 0 & \frac{-0.1116s + 0.01171}{s^2 + 0.03158s + 0.0001268} & 0 \\ 0 & 0 & \frac{-0.07862s + 0.003329}{s^2 + 0.02899s + 0.0001161} \end{bmatrix} \quad (15)$$

In the control design phase, the weighting parameters of the three controllers in the latent space are chosen as:

$$W_{11} = \frac{0.26}{1000s + 0.01}, \quad W_{12} = 10^{-4}, \quad W_{13} = \frac{2.5s}{0.01s + 1} \quad (16)$$

$$W_{21} = \frac{0.26}{1000s + 0.01}, \quad W_{22} = 10^{-4}, \quad W_{23} = \frac{2.5s}{0.01s + 1} \quad (17)$$

$$W_{31} = \frac{0.26}{1000s + 0.01}, \quad W_{32} = 10^{-4}, \quad W_{33} = \frac{2.5s}{0.01s + 1} \quad (18)$$

where W_{r1} ($1 \leq r \leq 3$) acts on the sensitivity function and must be large enough for low frequencies; W_{r2} is used to penalize the control action and it can be small; W_{r3} acts on the complementary sensitivity and should be large for high frequencies.

To investigate the performance and the advantages of the proposed method, the PID controllers within the same PLS framework are included. The parameters of PID controllers are tuned by the NCD toolbox of Matlab software. There have been a lot of successful applications of Matlab [34-37]. Three cases, including set-point tracking, disturbance rejection, and model errors, are tested respectively for the comparisons between the proposed method (PLS-H₂) and PLS-PID.

Case1: Tracking ability test in the nominal operating condition

In this part, the control system is evaluated by imposing sudden step changes of the set-point values:

- (1). The set-point of the power output N is decreased from 100kW to 97 kW at 1,000s, and then is increased from 97kW to 102kW at 2,000s.
- (2). The set-point of the evaporating pressure P_e is increased from 2MPa to 2.005MPa at 1,000s, and then is decreased from 2.005MPa to 1.992MPa at 2,000s.
- (3). The set-point of the superheated vapor temperature at the outlet of evaporator T_{sh} is decreased from 137.6°C to 135.6°C at 1,000s, and then is increased from 135.6°C to 136.6°C at 2,000s.
- (4). The set-point of the temperature at the outlet of the condenser T_{ch} is increased from 31.7°C to 33.7°C at 1,000s, and then is decreased from 33.7°C to 30.7°C at 2,000s.

The results of the PLS-H₂ and the PLS-PID control strategies are shown in Fig. 4. All the plots in Fig. 4 indicate that the control objectives of both control strategies are improved gradually and they converge to the desired levels, but in the proposed PLS-H₂, the power output, evaporating pressure, temperature at the outlet of the evaporator and the condenser can follow the reference step changes quickly with high precision. The maximum deviations of N , P_e , T_{sh} and T_{ch} in PLS-H₂ control are 0.27kW, 0.018MPa, 2°C and 0.2°C respectively; their maximum deviations of N , P_e , T_{sh} and T_{ch} in PLS-PID control are no more than 0.17kW, 0.002MPa, 1°C and 0.2°C respectively;. The proposed controller can drive the CVs back to their set-points with smaller overshoot than the PLS-PID algorithm. Meanwhile, the variations of the manipulated variables in the proposed PLS-H₂ shown in Fig. 5 are reasonable and feasible.

In Ref [17], a linear quadratic regulator (LQR) with PI controllers is applied to organic Rankine cycles in waste heat utilizing processes. The type of multivariable control is known as centralized control. The optimization needs to be performed online; this means that the control law needs to be computed and updated at every sampling time. Also, it only considered the set-point tracking and the disturbance rejection of the ORC control system instead of the robustness of the control system. Unlike centralized control, the proposed control method is a multi-loop control scheme and it can be designed offline. Taking into account model mismatch and disturbances from the heat source, the robust H₂ controller is designed. It has less computational burden and a high fault-tolerance performance. It is not only convenient but also practical. For fair comparisons, LQR with PI controllers is applied to the same testing cases. To save space, only step set-point changes are shown in Fig. 6 and Fig. 7. The testing results indicate that the LQR method fails to achieve a satisfactory performance in the presence of noises.

In the ORC system, the produced electric power from the generator needs to follow the variations of the electric demand precisely and quickly with fewer input efforts. Thus, the operating efficiency is determined by the tracking performance of electric power. The integral time absolute error (ITAE) of all the controlled variables and the integral squared input change (ISI) for all the manipulated variables are

respectively chosen as the specifications of the control loop performance.

$$ITAE = \sum_i^4 \int_0^t t |e_i| dt \quad ISI = \sum_i^4 \int_0^t \Delta u_i^2 dt$$

Table 2 indicates that the proposed method achieves a satisfactory tracking performance with the fewest changes of the manipulated inputs.

Case 2: Disturbance rejection test

In order to verify the effectiveness of disturbance rejection capabilities of the proposed control scheme, two ORC system disturbances commonly occurred are applied, respectively:

- (1). The turbine side is disturbed by applying step changes on the throttle valve opening.
- (2). The heat transfer process in the evaporator is disturbed by the mass flow rate of exhaust gas.

In the first scenario of the disturbance, at $t = 500s$ a step change of 2% magnitude in the valve opening is made; at $t = 2000s$, a step change of -2% magnitude in the valve opening is made.

In Figs. 8-9, there is an immediate change in the power output in response to a change in the throttle valve opening. Being a highly coupled system, the rest of the CVs also experience transient fluctuations. The maximum deviations of N , P_e , T_{sh} and T_{ch} in PLS-PID control are 0.2kW, 0.04MPa, $2^\circ C$ and $2^\circ C$, respectively; the maximum deviations of N , P_e , T_{sh} and T_{ch} in PLS-H₂ control are no more than 0.2kW, 0.036MPa, $1.8^\circ C$ and $1.8^\circ C$, respectively. All the CVs restore to their set-points swiftly again. The MVs are all kept within proper ranges. Though PID controllers can track the set-point better than the proposed controller, the MVs have fairly large variations.

In the second scenario of the disturbance, the mass flow rate of the exhaust gas disturbances is simulated, and $\pm 3\%$ step changes are applied at 500s and 2,000s respectively as shown in Figs. 10-11. Their maximum deviations of N , P_e , T_{sh} and

T_{ch} in PLS-PID control are 0.4kW, 0.008MPa, $1^{\circ}C$ and $0.5^{\circ}C$, respectively; the maximum deviations of N , P_e , T_{sh} and T_{ch} in PLS- H_2 control are no more than 0.3kW, 0.007MPa, $0.9^{\circ}C$ and $0.4^{\circ}C$, respectively and they return to the set-point quickly again.

Case 3: Robust performance test

The robustness of the H_2 controller is tested in simulation by varying system parameters from their nominal values. The results for step changes of references are plotted in Figs. 12-13, with a deviation range of $\pm 20\%$ for system parameters. The plots show that the proposed control method can handle strong deviations in the system parameters. The performance is still acceptable even with model mismatch. The simulation results indicate that the proposed PLS- H_2 controller has shorter settling time and smaller overshoot compared with the PLS-PID controller in the set-point tracking test with the perturbed models. In order to quantitatively compare the two control methods, the numerical ITAE and IIS are shown in Table 3. It is found that the values of ITAE in Table 3 are the same as those in Table 2. This means these two methods can work well for the perturbed ORC system. However, from the viewpoint of the IIS values, the proposed PLS- H_2 control method has better set-point tracking ability with fewer input efforts.

6. Conclusion

Without adding new measurements, it is difficult to reduce uncertainties of the ORC system. Taking into account model mismatch and disturbances, this paper presents a multi-loop robust H_2 control method with the PLS framework for a 100kW waste heat recovery process using the ORC system. Three different kinds of simulation tests have been carried out in order to test the control performance. The following conclusions can be drawn

- 1) With the PLS control framework, the ill-conditioned WHECS is decoupled into several single control loops in the latent space. The difficulty of loop pairing of the controlled and manipulated variables for conventional decoupling control design is avoided. The PLS model is built offline for one time and then the model can be directly used for controller design.

- 2) The multi-loop robust control strategy keeps the process variables within safe operating limits despite variations in the set-points and the fluctuations of the waste heat source.
- 3) Robustness of WHECS is improved in the presence of model mismatch.
- 4) The proposed decentralized control strategy can be designed offline and easily implemented and adjusted in industrial plants.

As ORC is a nonlinear process, with the changes of the operating conditions, the nonlinearity of ORC system and the input and the output constraints should be considered. This will be studied by introducing the nonlinear types of partial least squares in the future work.

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Table 1 Explained variance captured by each PLS latent variable

Explained variance captured by each PLS latent variable				
Input data block			Output data block	
L V	Explainedvarian ce (%)	Accumulated explainedvarian ce (%)	Explainedvarian ce (%)	Accumulated explainedvarian ce (%)
1	25.88	25.88	77.80	77.80
2	27.67	53.53	18.84	96.64
3	25.65	79.19	2.25	98.0
4	20.81	100.00	1.11	100.00

Table 2 Tracking errors in disturbance rejection test

	PLS-robust	PLS-PID	LQR
ITAE	276	282	99
ISI	1.01	1826	1.78×10^8

Table 3 Tracking errors in model mismatch

	PLS-robust	PLS-PID
ITAE	276	282
ISI	1.01	1826

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(a)

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(b)

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5 Fig. 1(a) An ORC system diagram, and (b) a typical T-s process diagram for the ORC system

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Fig. 2 Multi-loop robust control scheme in PLS framework

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Fig. 3 Mixed sensitivity configuration in one PLS subspace

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Fig. 4 Control responses to step set point changes

Fig. 5 Variations of the manipulated variables in step set point changes

Fig. 6 Control responses to step set point changes (LQR)

Fig. 7 Variations of the manipulated variables in step set point changes (LQR)

Fig. 8 Control responses to disturbance from the valve position

Fig. 9 Variations of the manipulated variables in disturbance from the valve position

Fig. 10 Responses to the disturbance from the mass flow rate of exhaust gas

Fig. 11 Variations of the manipulated variables in the disturbance from the mass flow rate of exhaust gas.

Fig. 12 Control responses to set-points changes for the perturbed system

Fig. 13 Manipulated variables response to set-points changes for the perturbed system

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