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Optimizing Control Strategy of S-CO_2 Cycle for SFR Application by using Genetic Algorithm and Artificial Neural Network

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1. Introduction

The Supercritical CO_2 (S-CO_2) power cycle use S-CO_2 as a working fluid. For conventional Sodium-cooled Fast Reactor (SFR) design, violent reactions of sodium-water can be a safety issue. The S-CO_2 power cycle can improve safety by replacing violent sodium-water reactions with mild sodium-CO_2 reactions. As a result, S-CO_2 power cycles have been studied for SFR application. Since S-CO_2 has density close to liquid and viscosity close to gas, thus the power system has compact equipment and power consumption for compression is minimized. The idea of S-CO_2 power cycles is to approach the inlet condition of the compressor towards the critical point which is 31.3℃ and 7.37MPa to improve cycle efficiency.

Engineers design power cycles assuming all devices and conditions are at the steady state. In case of S-CO_2 power cycle, turbine inlet temperature and compressor inlet temperature are assumed to be 505℃ and 31.3℃, respectively. However, it is not easy to maintain on-design conditions in real operation. When demand of electricity or heat sink temperature changes, load on turbine or compressor inlet temperature can change. Under these circumstances, power cycle can operate in off-design conditions. Thus, an off-design analysis is necessary to identify the best operation strategy.

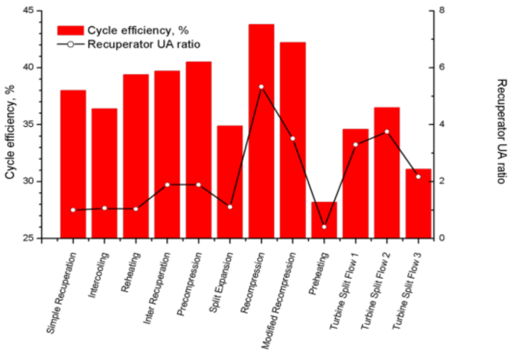

Fig. 1. Performance comparison of S-CO_2 cycle layout [3]

KAIST research team developed an S-CO_2 steady state cycle analysis code (KAIST-CCD) and turbine / compressor / heat exchanger codes for off-design analysis (KAIST-HXD, KAIST-TMD). Carsten (2007) conducted various transient analyses of a single shaft S-CO_2 cycle in off-design conditions including part-load operation, loss-of-load, and more. Next, Trinh (2009) performed in off-design conditions a quasi-steady state analysis of turbomachinery operational stability. Yoon Han Ann (2016) reconfirmed that the recompression S-CO_2 cycle has the highest efficiency among several layouts under design conditions. He confirmed triple-shaft S-CO_2 cycle`s efficiency is higher than that of single-shaft S-CO_2 cycle and conducted a quasi-steady state analysis and transient analysis under off-design conditions. Off-design conditions of the S-CO_2 cycle can be induced due to many reasons. There are situations where the load on the turbine varies, the temperature of the heat sink changes due to climate reason, and regular start-ups and shutdowns. Since maintaining the inlet condition of the compressor near the critical point is one of the core ideas of this power cycle, the performance of the cycle is affected by the rapid change of the property when the inlet condition of the compressor is fluctuating.

In this study, the heat sink temperature change off-design conditions (compressor inlet temperature: 35℃) will be studied. Preliminary studies have made it possible to analyze the cycle in off-design conditions but it has not optimized for the maximum efficiency (best operation strategy) in that situation. Jiangfeng Wang (2010) used a genetic algorithm and artificial neural networks to optimize parameters for achieving the maximum exergy efficiency in a simple supercritical CO_2 cycle. In this study, the same method is used to optimize the cycle under off-design conditions.

2. Cycle modeling

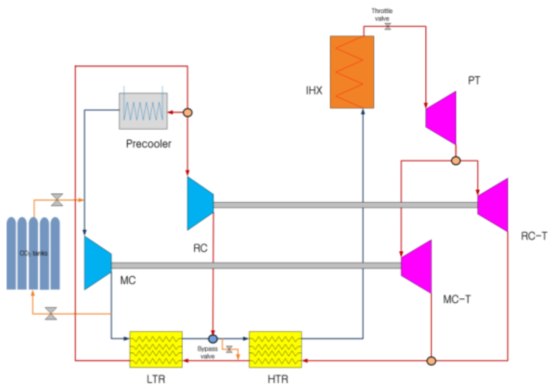

Fig. 2. Triple-shaft S-CO_2 cycle layout

Fig. 2 is a layout of a triple-shaft S-CO_2 cycle. This cycle has main compressor (MC), re-compressor (RC), one cooler, two recuperator (High temperature recuperator (HTR), Low temperature recuperator (LTR)), one intermediate heat exchanger (IHX) and three turbine (Power turbine (PT), MC turbine (MC-T) and RC turbine (RC-T)). In the case of a single-shaft, both compressors and turbines have the same RPM, while in the triple-shaft cycle configuration, each shaft can have different RPMs. The ability to have different RPMs allows to increase the efficiency due to increase of the freedom in operation. Thus, in this study the triple-shaft configuration is used and is conducted under the condition of equipment performance and system constraints such as Table. 1. System minimum pressure, RPM of MC and RPM of RC are used as control parameters. Therefore, these parameters will be optimized for the off-design condition when the compressor inlet temperature is at 35℃.

Table. 1. Cycle information

	Value
Machine Property	
PT Efficiency (%)	90
MC-T Efficiency (%)	90
RC-T Efficiency (%)	90
MC Efficiency (%)	80
RC Efficiency (%)	80
HTR Effectiveness (%)	95
HTR Hot side Pressure drop (kPa)	47
HTR Cold side Pressure drop (kPa)	60
LTR Effectiveness (%)	95
LTR Hot side Pressure drop (kPa)	46
LTR Colde side Pressure drop (kPa)	20
Cooler Pressure drop (kPa)	40
IHX Pressure drop (kPa)	20
System Information	
System Thermal Input (MW)	250
System Maximum Pressure (MPa)	20
Compressor Inlet Temperature (℃)	35
System Minimum Pressure (kPa)	Optimized
MC RPM	
RC RPM	

3. Quasi-steady state analysis

Cycle off-design analysis methodology can be divided into transient analysis and quasi-steady state analysis. Quasi-steady state analysis is a methodology that assumes that there is sufficient time interval between each transition, and assumes the beginning and end of the transition process as steady state. This method does not predict the transition state, but it can obtain the numerical solution in a relatively short time. Therefore, it is suitable for the gradual and slow transition state analysis such as heat sink temperature change and narrow width output change.

3.1 Heat exchanger off-design model

Off-design analysis models of heat exchanger and turbomachinery, which are components of the cycle, are necessary for quasi-steady state analysis. The Logarithm mean temperature difference (LMTD) methodology is one of the most widely used methodologies for the analysis of off-design performance of heat exchangers. However, since S-CO_2 exhibits abrupt changes in material properties near the critical point, the LMTD methodology derived from the assumption of constant material properties is unsuitable. Seong-Min Son (2017) analyzed IHX which operated relatively far from the critical point using LMTD methodology and HTR/LTR using finite difference method (FDM).

3.2 Turbomachinery off-design model

Seong Min Son (2017) used KAIST-TMD developed by KAIST research team to make off-design map of S-CO_2 turbomachinery. The KAIST-TMD code is a 1D mean line turbomachinery design code that uses the corrected mass flow rate concept.

4. Optimization methods

4.1 Genetic algorithm

Genetic algorithms are a search algorithm using genetic evolution based on survival of the fittest, in which the most appropriate members are selected from a given population and they are used to generate the next generation. In the genetic process, the gene that best adapts to the given environment is selected, crossed, and sometimes mutated to deliver the better genetic traits to the next generation. In search of the optimum by a genetic algorithm, a search is composed of the unit of population instead of a single element. Furthermore, a fitness function is used and a stochastic mutation rule is applied to the search algorithm. A fitness function, which is also a performance criterion, is used to select the best solution within population and to set parent for the descendants that make up the next generation.

Genetic algorithms use selection, crossover, and mutation operations. The selection operator is an operator for selecting two parent solutions for the crossover. There are various selection operators, but a common principle is that a good solution is likely to be chosen. The choice probability can be controlled by adjusting the difference in fitness between the good and the inferior solutions. The degree of this difference is called the selection pressure.

If the selection pressure is higher, the convergence is faster, and if the selection pressure is lower, the average quality of the population will not improve. In this study, the quality proportional roulette wheel, which is the most widely used selection method, is used. The fitness of the solution i in the solution group is calculated by the following equation.

$$f=-(N-i+(N-M)/(k-1)),\ k=3$$

Here, increasing the value of k increases the selection pressure. Generally, the value of k is 3 or 4. A roulette wheel selection based on this fit value is conducted. There is a roulette wheel with a size equal to the sum of the fit of each chromosome, each chromosome has an assigned space proportional to its fitness on the roulette wheel. Next, a simple arithmetic crossover is used as the crossover operator. In the case of the mutation operator, it is set to the probability that *1* will be selected when the uniform distribution is used between 1 to 20. Finally, efficiency is used as the objective function to represent the solution.

Table. 2. Genetic algorithm conditions

Gene	Real number
Selection Operator	Roulette Wheel
Fitness Function	$f=-(N-i+(N-M)/(k-1))$, $k=3$
Crossover Operator	$o_1=ap_1+(1-a)\,p_2$ $o_2=(1-a)\,p_1+ap_2$
Mutation Operator	Uniform Distribution
Objective Function	Efficiency

4.2 Artificial neural network (ANN)

Artificial neural networks perform learning from experience and have the ability to generalize from given training data to unknown data. In addition, the operation is performed quickly and can be used for real-time operation. An artificial neuron model is calculated by adding the results of multiplication of weights to the inputs to be introduced and applying them to the transfer function. Artificial neural networks typically have a multilayer structure consisting of an input layer, one or more hidden layers and an output layer. Each hidden layer has the same type of transfer function. In MATLAB's multilayer neural network, a sigmoid transfer function is generally used. A backpropagation neural network is one of the most widely used neural networks. In backpropagation learning, weight and bias values according to the development of multi-layer structure are repeatedly calculated. In this study, a feedforward net neural network embedded in MATLAB is used. Feedforwardnet can be used for all kinds of input-output mapping and has the arguments hiddensize and trainFcn. Each means the column vector size and training function of the hidden layer and has 10 and trainlm as the defult values. Trainlm is a training function that updates weights and biases according to Levenberg-Marquardt optimization. Trainlm is often the fastest backpropagation algorithm in the toolbox and requires more memory than other algorithms, but it is used first in supervised algorithms.

Table. 3. Artificial neural network conditions

Neural Network	Feedforwardnet
Training Function	Trainlm (Levenberg-Marquardt optimization

5. Off-design analysis

5.1 Collection of sample

There is the system minimum pressure-system net work graph according to compressor inlet temperature in paper of SeongMin Son (2017). Based on this data, the range of control parameters are set. The basic RPM of turbines is 7200. Table. 4 shows the range of them. Efficiency, net work, mass flow rate and split ratio are obtained through the values selected randomly within ranges and the physical model code using off-design model suggested above. This process is repeated to collect about 3000 samples.

Table. 4. Range of control parameters

Control Parameters	Range
System Minimum Pressure	8090 ~ 8942
MC RPM	6500 ~ 7500
RC RPM	6500 ~ 7500

5.2 Artificial neural network

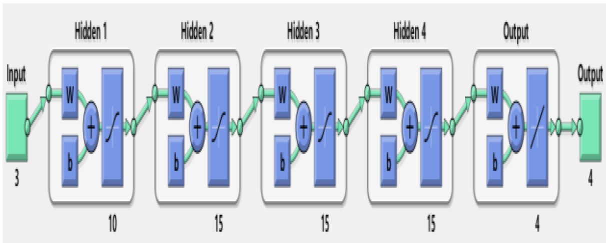

Fig. 3. Multilayer neural network in MATLAB

Since the physical model code takes long time for obtaining the solution, it is replaced with an artificial neural network. Fig. 3 shows the learning structure of artificial neural network. Inputs are system minimum pressure, MC RPM and RC RPM. Outputs are net work, efficiency, mass flow rate and split ratio. 3000 samples are prepared, 80% of the samples is used for learning, 10% of for checking validation and 10% for the final testing. The overall appearance of the artificial neural network uses four hidden layers, and each layer has 10, 15, 15, and 15 nodes, respectively. The numbers of these nodes and layers are not fixed. They can be changed for better learning in other cases.

Table. 5. Artificial neural network conditions

Number of samples	3000
Learning	80%
Validation	10%
Testing	10%
Number of Nodes in Input layer	3
Number of Hidden layers	4
Number of Nodes in Each hidden layer	10 15 15 15
Number of Nodes in Output layer	4

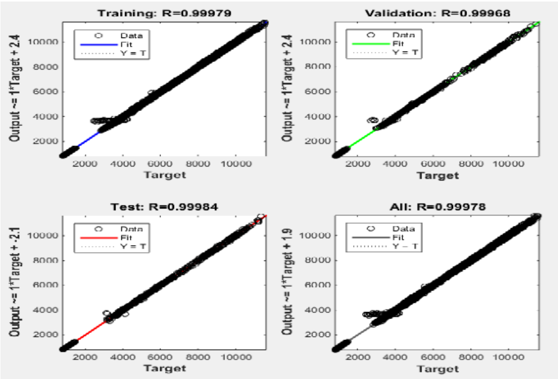

Fig. 4. Regression of neural network in MATLAB

Fig. 4 shows the result of learning according to the conditions described above. If the learning is successful, the data will be placed along 45 degree line (i.e. y = x line) as shown. Also, if the R value is greater than 0.93, it is reasonably well fitted ANN.

5.3 Genetic algorithm

Table. 6. Off-design result before optimization

System Minimum Pressure	8516
MC RPM	7200
RC RPM	7200
Efficiency	42.1386

Table. 7. Off-design optimization result

System Minimum Pressure	8074	8277	8120
MC RPM	7362	7300	7264
RC RPM	6828	6759	6805
Efficiency	44.44	44.31	43.86
Physical model code	43.5498	43.5763	43.5096

Table. 6 shows the results before optimization and Table. 7 shows the results of optimization using the described genetic algorithm. The efficiency increases from about 42% to 43.5%. Operating strategy by lowering the system`s minimum pressure, increasing the RPM of the MC, and lowering the RPM of the RC can be determined from the optimization results.

6. Conclusions

In this study, a method of using genetic algorithm and artificial neural network to optimize the operation strategy in the off-design condition is proposed and a triple-shaft S-CO_2 cycle is considered. System minimum pressure, main compressor RPM, and recompressor RPM are used as control parameters. Quasi-steady state analysis is used and the case where the heat sink temperature changes is investigated. In this case (compressor inlet temperature is 35℃), the results suggest that main compressor RPM should be increased while the minimum pressure and re-compressor RPM are reduced to maintain the best performance of the power system.

In the future, the developed platform will be used for analyses of various off-design conditions and optimizations of control strategy for each analyzed condition.

7. Acknowledgments

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8. Reference

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