Neural networks for small scale ORC optimization

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Contents

What is a Neural Network (NN)?

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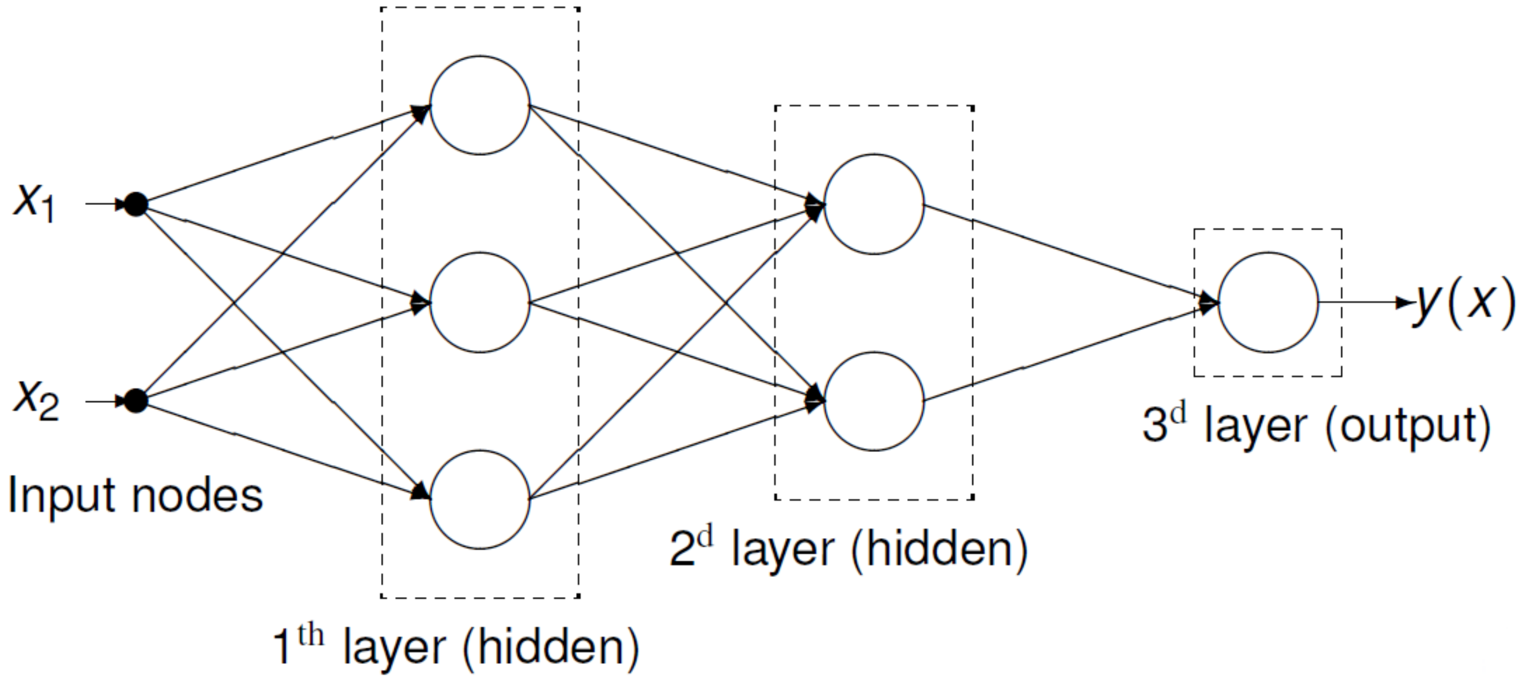
- A neural network is composed of many artificial neurons that are linked together according to a specific network architecture
- The objective of the neural network is to transform the inputs into meaningful outputs.



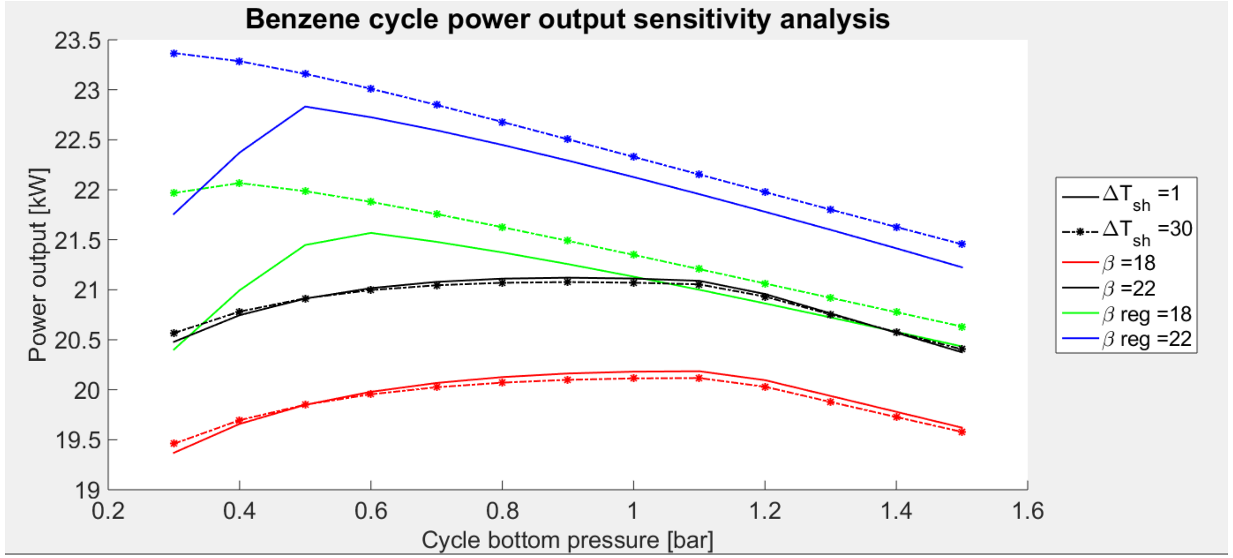
Why NN for ORC optimization?

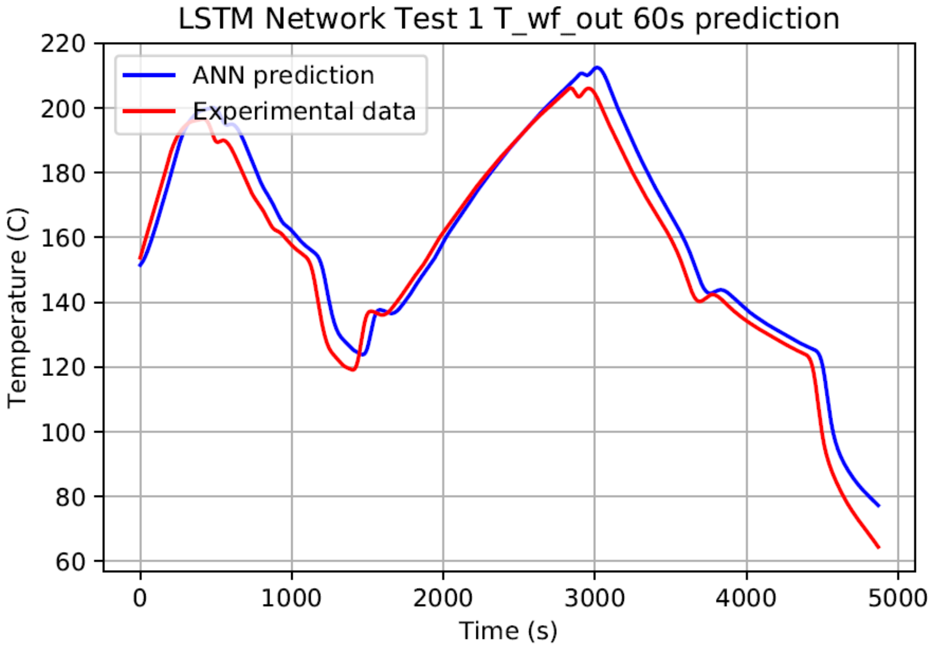
- ORC optimization is a highly non-linear optimization problem
- Common optimizers cannot use the derivative of the objective function to move towards the optimal solution (black box algorithms)
- Neural Networks rebuild the objective function and constraints of an optimization problem as differentiable equations; this allows NNs to use the derivatives during the optimization process
- More reliable results and reduced computational time with respect to traditional optimization algorithms (free derivative algorithms, genetic algorithms, etc.)

Neural Networks for the optimization of ORC systems

Applications of NNs for the optimization of ORC systems

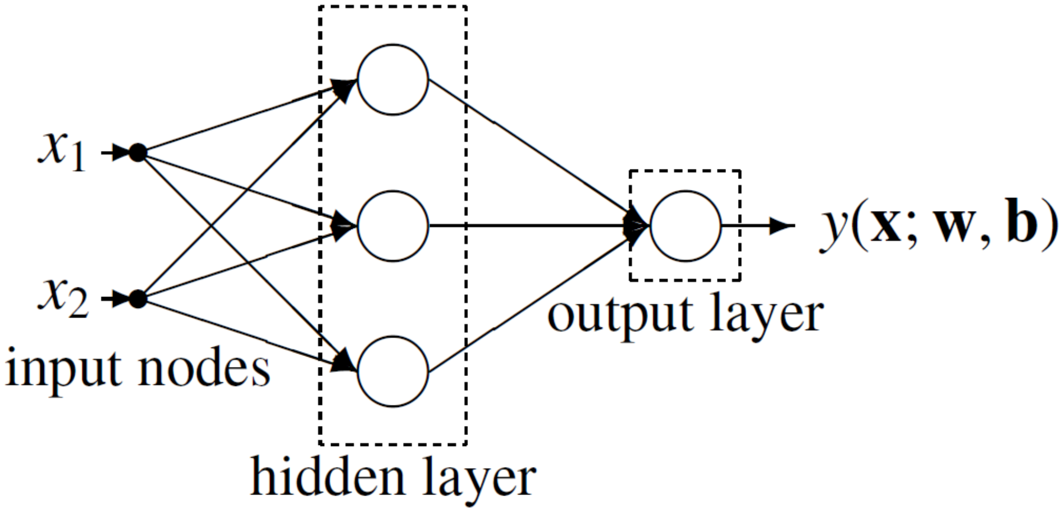
- Definition of the turbine efficiency as a function of the cycle's parameters
- Techno-economic optimization of non linear processes
- Dynamic prediction using experimental data
- Optimal Control
- Fault detection





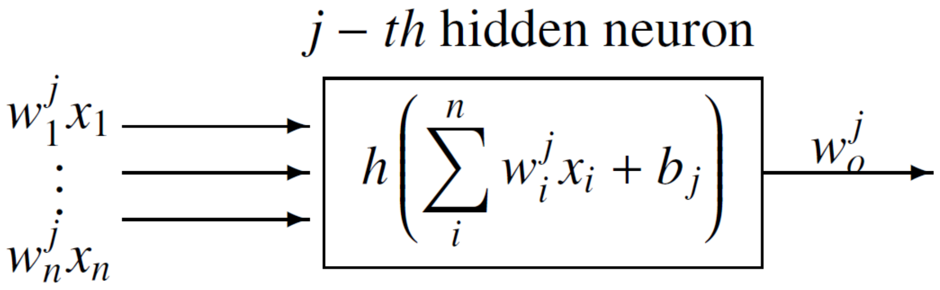
Architecture of a basic Neural Network

- n: number of neurons in the hidden layer
- m: number of neurons of the output
- w_i^j: weight of the arc connecting input node with neuron j of the hidden layer
- w_o^j: weight of the arc connecting hidden neuron j to the output
- b_j: threshold of hidden neuron j
- b_o: threshold of the output neuron
- h: activation function of the hidden neurons (the activation function of the output neuron is a linear function of the inputs)



The output of the network $y(x; w, b)$ is defined as:

$$y(\mathbf{x}; \mathbf{w}, \mathbf{b}) = \sum_j^m w_o^j h\left(\sum_i^n w_i^j x_i + b_j\right) + b_o$$



Neural Networks' model

Training the Neural Network

The output of the network $y(x)$ is defined as:

$$y(\mathbf{x};\mathbf{w},\mathbf{b}) = \sum_{j}^{m} w_o^j h\left(\sum_{i}^{n} w_i^j x_i + b_j\right) + b_o$$

The training of the network consists in solving an optimization problem, in which the error of the network in predicting the instances of the training set is minimized

$$\min_{\mathbf{w},\mathbf{b}} E(\mathbf{w},\mathbf{b}) = \frac{1}{2}\sum_{p}^{P} \left\|\bar{y}_p - y(\mathbf{x}_p;\mathbf{w},\mathbf{b})\right\|^2$$

Neural Networks’ model

Design of the Neural Network

- Definition of the training set (x^p, y^p)
- Definition of the parameters of the network (Network architecture, Error function, Number of neurons, activation function etc.)
- Training of the Neural Network

$$x_p \longrightarrow \boxed{\quad f(x) \quad} \longrightarrow y_p$$

- Test of the Neural Network

$$x \longrightarrow \boxed{\quad f(x) \quad} \longrightarrow y$$

Optimization problem

ORC model of the thermodynamic cycle

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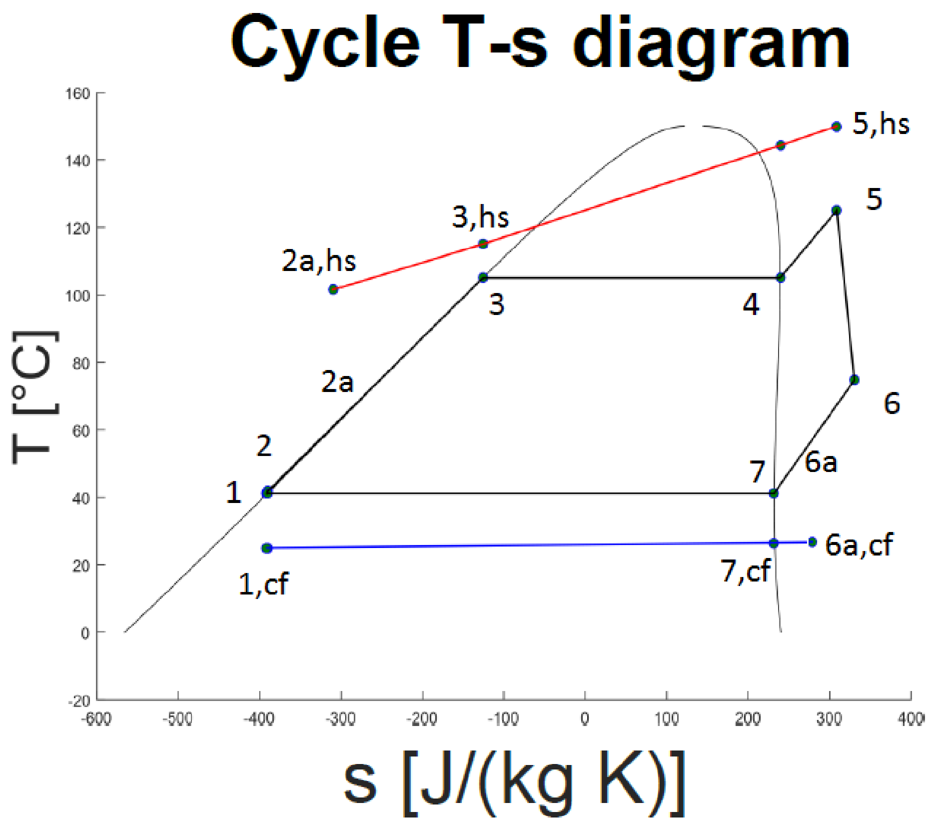
MASS CONSERVATION EQUATIONS

Heat source	$\dot{m}_{hs} = const$	(1)
Working fluid	$\dot{m}_{wf} = const$	(2)
Cooling fluid	$\dot{m}_{cf} = const$	(3)

ENERGY BALANCE EQUATIONS

Evaporator	$\dot{m}_{hs} * \left(h_{5,hs} - h_{2a,hs}\right) = \dot{m}_{wf} * (h_5 - h_{2a})$	(4)
Turbine	$P_{turbine} = \eta_{turbine} * \dot{m}_{wf} * (h_5 - h_6)$	(5)
Condenser	$\dot{m}_{wf} * \left(h_{6a,wf} - h_{1,wf}\right) = \dot{m}_{cf} * \left(h_{6a,cf} - h_{1,cf}\right)$	(6)
Regenerator	$\dot{m}_{wf} * (h_6 - h_{6a}) = \dot{m}_{wf} * (h_{2a} - h_2)$	(7)
Pump	$P_{pump} = \dfrac{\dot{m}_{wf} * (h_2 - h_1)}{\eta_{pump}}$	(8)



Optimization problem

Boundary conditions

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- $\Delta T = 10\ K$
- $U_{turbine,in} = 400 \frac{m}{s}$
- $\psi_{turbine,in} = 1$
- $\psi_{turbine,out} = 0$
- $\boldsymbol{\omega}_{turbine}^{max} = 30000\ rpm$
- $T_{wf,limit} = 400\ K$
- $\eta_{pump} = 0.8$
- $n_s = 0.55$

$$W_{turbine} = \psi_{in} U_{turbine,in}^2$$

$$\boldsymbol{\omega}_{turbine} = \frac{n_s\, W_{turbine}^{0.75}}{\sqrt{Q_{turbine,out}}}$$

- Working fluid: R 1234yf
- Heat source: Water
- Heat source temperature: 413.15 K
- Heat source mass flow rate: 3.2 kg/s
- Subcritical cycle
- Pressure drop in the heat exchangers neglected

Optimization problem

Using the NN to solve the Optimization model

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$$\max_{x \in \Omega} \quad (P_{turbine} - P_{pump}) = P_{cycle}$$

$$\min_{x \in \Omega} \quad (UA_{evaporator} + UA_{condenser} + UA_{regenerator}) = UA_{sum}$$

$$\min_{x \in \Omega} \quad \omega_{turbine}$$

subject to

$$\left.\begin{aligned} & T_i - T_{i,cf} \geq \Delta T \ , \ i = 1,7 \\ & T_{6a} - T_{6a,cf} \geq \Delta T \\ & T_{2a,hs} - T_{2a} \geq \Delta T \\ & T_{i,hs} - T_i \geq \Delta T \ , \ i = 3,5 \\ & T_6 - T_{2a} \geq \Delta T \\ & T_{6a} - T_2 \geq \Delta T \end{aligned}\right\} \text{Avoid the violation of the 2nd law of thermodynamics}$$

$$\left.\begin{aligned} & T_5 \leq T_{limit} \\ & T_{2a,hs} \geq T_{limit,hs} \end{aligned}\right\} \text{Avoid the deteriorations of fluid}$$

$$\left.\begin{aligned} & T_7 \leq T_{6a} \leq T_6 \\ & T_2 \leq T_{2a} \leq T_3 \end{aligned}\right\} \text{Regeneration in the single phase region}$$

$$\left.\begin{aligned} & W_{turbine} \leq W_{turbine}^{max} \\ & \omega_{turbine} \leq \omega_{turbine}^{max} \end{aligned}\right\} \text{Technical constraints}$$

$$P_{cycle} \geq P_{cycle}^{target}$$

DECISION VARIABLES (x_p)

Working fluid mass flow rate	$\dot{m}_{wf}$
Bottom pressure of the ORC cycle	$p_{bottom} = p_2$
Top pressure of the ORC cycle	$p_{top} = p_1$
Super-heating rate	$\Delta T_{sh} = T_5 - T_4$
Turbine efficiency	$\eta_{turbine}$
Degree of regeneration	$R = \dfrac{h_6 - h_9}{h_6 - h_7}$

Optimization problem

Using the NN to solve the Optimization model

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$$P_{cycle} \geq P_{cycle}^{target}$$

Neural Network →

$$P_{cycle} = f(x_p)$$
$$UA_{sum} = f(x_p)$$
$$\boldsymbol{\omega}_{turbine} = f(x_p)$$

Each variable of the optimization problem is expressed using a **different** neural network

DECISION VARIABLES (x_p)

Working fluid mass flow rate	$\dot{m}_{wf}$
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Optimization problem

Definition of the training set and of the parameters of the network

Parameters of the network

- Multi layer perceptron (MLP) network
- 20 Neurons in the hidden layer
- K-fold cross validation
- Approximated Sigmoid function as the activation function

Definition of the training set

- Examples defined using the ORC thermodynamic model (x_p, y_p)
- Each variable of the optimization problem is represented by a neural network that expresses it as a function of the decision variables

Results of the training of the Neural Network

	mean	standard deviation
correlation coefficient	0.9995	0.0022
relative absolute error	0.7981%	0.8741%

Results

Optimal solutions of the problem

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Solution of the optimization problem using Neural Networks

$\dot{m}_{wf}$ [kg/s]	p_{bottom} [bar]	p_{top} [bar]	ΔT_{sh} [K]	η_{turb} [-]	RD [-]	P_{cycle} [kW]	UA_{sum} [kW/K]	$\omega_{turbine}$ [rpm]	time [s]
3.24	11.73	33.82	10.81	0.75	0.3	**35.19**	53	30000	23.87
2.91	11.73	33.82	10.93	0.75	0.25	31.67	**44.15**	30000	106.56
3.51	11.75	28.79	5.32	0.75	0.15	31.67	55.34	**24298**	100.14

Solution of the optimization problem using a Free Derivative Algorithm

$\dot{m}_{wf}$ [kg/s]	p_{bottom} [bar]	p_{top} [bar]	ΔT_{sh} [K]	η_{turb} [-]	RD [-]	P_{cycle} [kW]	UA_{sum} [kW/K]	$\omega_{turbine}$ [rpm]	time [s]
3.11	11.74	33.72	14.26	0.75	0.001	**36.65**	54.3	30000	343.45
3.01	12.28	33.72	12.97	0.75	0.2	32.99	**45.06**	30000	470.49
3.4	11.74	29.87	7.14	0.75	0.001	32.98	61.96	**25646**	465.83

- The results obtained solving the optimization problem using Artificial Neural Networks have been compared to those obtained using a free derivative optimization algorithm
- Neural Networks reduce the computational time needed to solve non-linear optimization problems

Results

Optimal solutions of the problem

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Solution of the optimization problem using Neural Networks

$\dot{m}_{wf}$ [kg/s]	p_{bottom} [bar]	p_{top} [bar]	ΔT_{sh} [K]	η_{turb} [-]	RD [-]	P_{cycle} [kW]	UA_{sum} [kW/K]	$\omega_{turbine}$ [rpm]	time [s]
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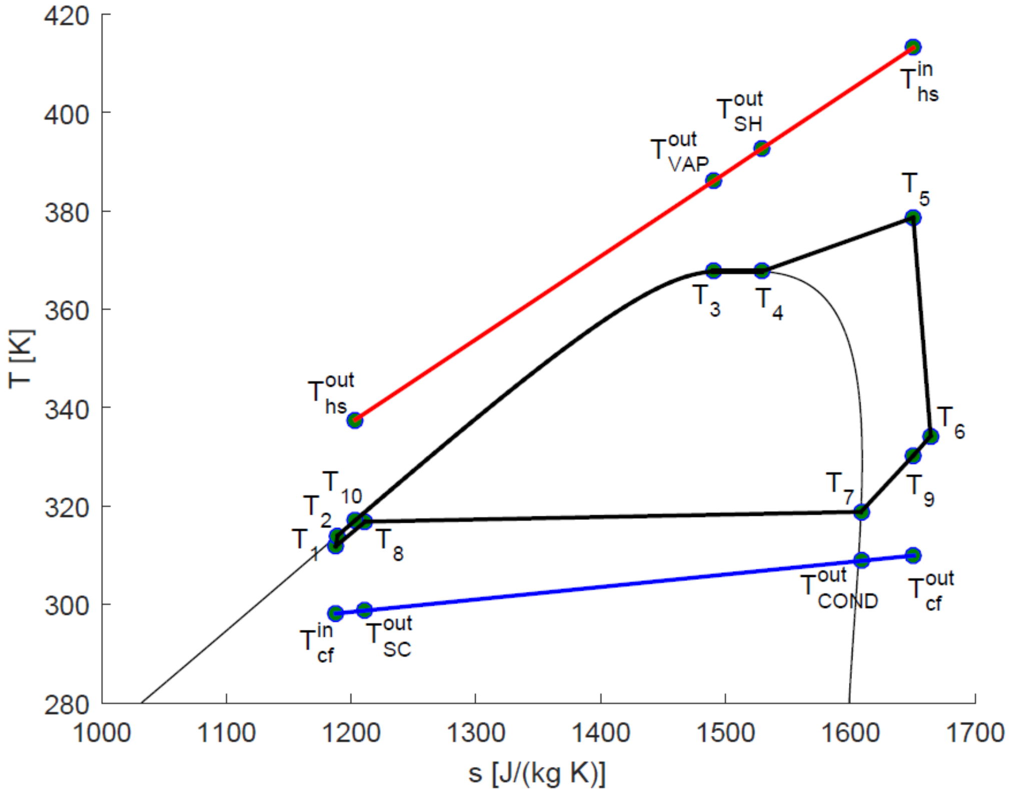
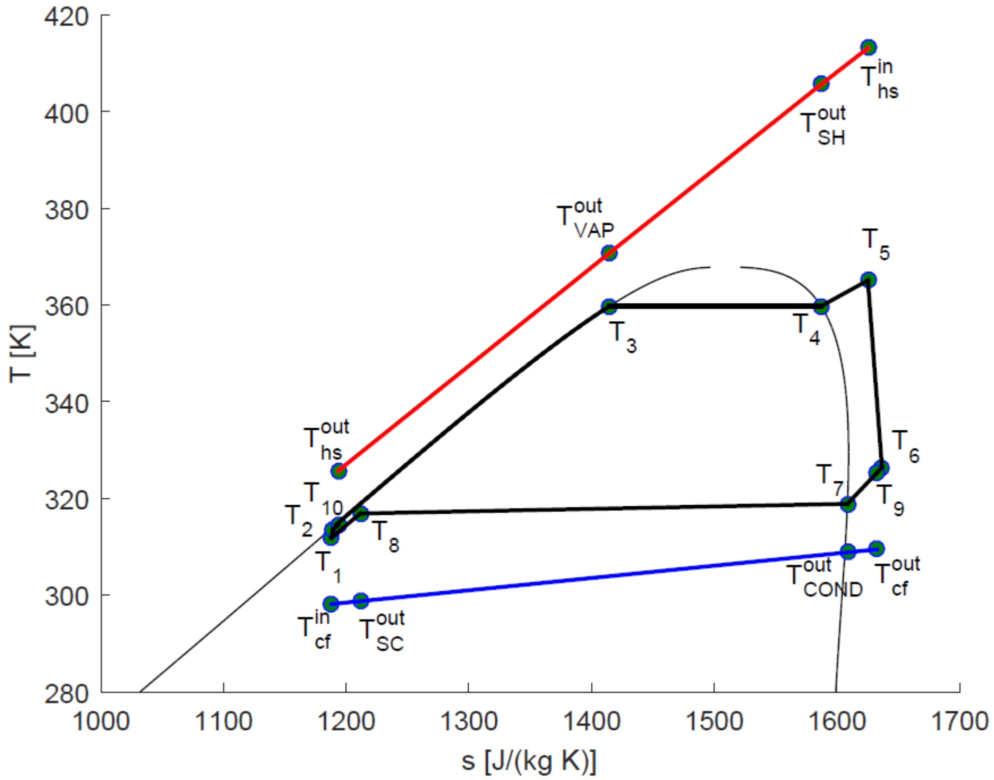
Results

Optimal solutions of the problem

$\min UA$



$\min rpm$



Conclusion

Results:

- Neural Networks have been used to perform ORC system Optimization
- The results show that Neural Networks can speed up the ORC optimization process, providing performance similar to commonly used optimization algorithms
- The convenience of using Neural Networks for ORC optimization increases as the non-linearity of the optimization problem increases (techno-economic optimization, size minimization etc.)

Future works:

- Thermo-economic optimization of ORCs using NN techniques
- Prediction of the dynamic behavior of ORC systems using experimental data to train the network
- Cost prediction of ORC components to be include in techno-economic analysis of ORC systems

Thank you for your attention!!!

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