AN ADAPTIVE NEURO-FUZZY MODEL OF A RE-HEAT TWO-STAGE ADSORPTION CHILLER

by

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Since the adsorption chillers do not use primary energy as driving source the possibility to employ low temperature waste heat sources in cooling energy production receives nowadays much attention of the industry and science community. However, the performance of the thermally driven adsorption systems is lower than that of other heat driven heating/cooling systems. Low coefficients of performance are one of the main disadvantages of adsorption coolers. It is the result of a poor heat transfer coefficient between the bed and the immersed heating surfaces of a built-in heat exchanger system.
The purpose of this work is to study the effect of thermal conductance values of sorption elements and evaporator as well as other design parameters on the performance of a re-heat two-stage adsorption chiller. One of the main energy efficiency factors in cooling production, i. e. cooling capacity for wide-range of both design and operating parameters is analyzed in the paper.
Moreover, the work introduces artificial intelligence approach for the optimization study of the adsorption cooler. The ANFIS was employed in the work.
The increase in both the bed and evaporator conductance provides better performance of the considered innovative adsorption chiller.
The highest obtained value of cooling capacity is 21.7 kW and it can be achieved for the following design and operational parameters of the considered re-heat two-stage adsorption chiller: M_{sorb} = 40 kg, *t* = 1300 s, *T* = 80 °C, C_{sorb}/C_{met} = 50, hA_{sorb} = 4000 W/K, hA_{evap} = 4000 W/K.

Keywords: *overall thermal conductance, combined cooling, heating and power, artificial intelligence, low temperature heat sources, ANFIS, adsorption chiller, reheat two-stage, bio-inspired modeling*

Introduction

Silica gel-water adsorption chillers provide the economically viable and environmentally friendly technology, capable to convert waste thermal energy into useful cooling [1]. They can be used, *e. g.* for air conditioning, grain depot cooling, combined cooling heating

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and power systems [2]. The main advantages of adsorption cooling systems, are: low driving temperatures they are operating with, the possibility to use RES or low temperature waste heat, practically no moving and rotating parts (except valves) leading to less vibration, less noise and quiet operation, environmentally friendly and very low maintenance requirements as well as simplicity and low cost of operation and control [1-3]. Their disadvantages are: the intermittence, bulkiness, and poor thermal conductivity of the used adsorbents, leading to the low specific cooling power (SCP) and COP [2].

Due to water adsorption and desorption processes SCP is consumed and released in the evaporator and the condenser, respectively [4]. Aristov *et al*. [4] pointed out, that for the SWS-1L composite, synthesized by impregnating $CaCl_2$ into mesoporous silica gel as a sorbent with large grains (1.4-16 mm) and vapor pressure 55-60 mbar the maximum specific power can reach 3.7 kW/kg_{sorb} whereas for water adsorption at lower pressures (10-15 mbar) the SCP was lower, in the range of 0.75-1.9 kW/kg_{sorb} [4].

Low operating pressure required by the adsorption chillers is also listed amount the disadvantages as it makes difficult to achieve air-tightness [2, 5].

Precooling, adsorption, preheating and desorption are the main phases during operation cycle of a simplest adsorption chiller. For the simple cycle, the most common control assumes equal duration of adsorption and desorption phases, however, since dynamics of desorption is faster than the adsorption one, the desorption phase should be shortened, allowing for longer adsorption times [5]. Similar observations were reported in [6]. Adsorption and desorption processes are quasi-isobaric and the typical pressure decrease in adsorption heat pumps do not exceeds 2-3 mbar [6]. The typical temperatures at which the evaporation process occurs are 5-20 ^{o}C [7]. The complex phenomena occurring in adsorption and desorption stages, are described inter alia in [8].

Since the complexity of multi-bed adsorption chillers operation is still not sufficiently recognized, the improvement of total efficiency of adsorption processes is still challenging task.

As constructing and operating complete set-ups with full size adsorbers is expensive and time consuming, the mathematical modeling approach constitutes an alternative method of data handling and the development of simple, non-iterative models of the chillers is of practical significance.

Generally two main dynamic models of adsorptive heat transformers (*e. g*. heat pumps, chillers) can be distinguished. The models can be classified as heat and mass transfer models and lumped parameters models [9]. The first group considers variation of the adsorbent temperature, pressure, and adsorbate concentration, both in time and space, whereas the lumped parameters models take into account a simplified representation of the adsorption process, neglecting any space gradients [9]. Three main equations, for: energy balance, mass balance, and adsorption equilibrium are taken into account in a common lumped parameters model [9]. Since the heat and mass transfer models require complex and time-consuming numerical methods for solving sets of PDE, the first models are not wide spread and the most popular are lumped parameters models [9].

As models usually need some additional data, *e. g*. to adjust coefficients, some parameters could not be determined immediately, especially for different operating conditions. Moreover, sometimes additional assumptions should be made to get a trackable solution, so the algorithms are often complicated and based on the solution of complex and time consuming sets of differential equations [10-12].

Artificial intelligence (AI) approach can be the alternative methods for the technics of data handling. The most convenient approach is to apply a non-iterative procedure, where one only needs to enter input parameters and call the performed the AI model.

The paper introduces the ANFIS for modelling of a re-heat two-stage adsorption chiller using low temperature heat from cogeneration in the range of 50-90 $^{\circ}$C. The developed non-iterative model, using procedure similar to the one given in [13-17] allows to describe the behavior of the adsorption cooler and predict one of the main energy efficiency factors in cooling production, *i. e*. cooling capacity (CC) for wide-range of both design and operating parameters.

The low heat source temperatures, for which the chiller can operate, is lower than the often exploit, above 55 $^{\circ}$C and stands for the innovative design of the cooler [18, 19].

To our best knowledge we are the first to employ the ANFIS to describe the behavior of the innovative adsorption chiller and predict one of the main energy efficiency factors in cooling production, *i. e*. CC for wide-range of both design and operating parameters.

Analysis and modelling

An object of investigations

The analyzed re-heat two-stage chiller consists of four adsorbent beds, one evaporator and one condenser as well as metallic tubes for heat transfer fluid and refrigerant flows [18, 19]. Silica gel-water constitutes a working pair. The schematic diagram of a re-heat two-stage chiller is given in fig. 1.

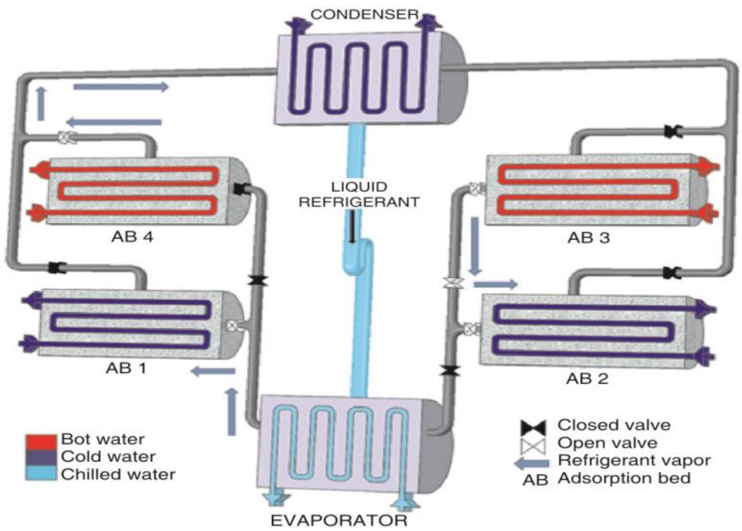

Figure. 1 The schematic diagram of the innovative re-heat two stage adsorption chiller (*for colour image see journal web site*)

The following main features constitute the innovative design of the considered re-heat two-stage adsorption chiller [20, 21]:

– the chiller provides more effective cooling production even for low heat source temperatures from the range of 50-90 $^{\circ}$C.

– contrary to the two-stage adsorption chiller without re-heat, where the evaporating pressure difference between condenser and evaporator is divided into two consecutive pressure lifts, the evaporating pressure lift in the re-heat two-stage adsorption chiller can be divided into different ways,
– contrary to the conventional two-stage adsorption chiller, in re-heat two-stage adsorption chiller the lower two beds and the upper two beds interact with condenser and evaporator, respectively, and
– the COP of the cooler is higher than that of two-staged chiller without re-heat.

One full operating cycle consists of six consecutive steps: desorption, mass recovery process with heating, pre-cooling, adsorption, mas recovery process with cooling and pre-heating. All beds undergo through all previously listed steps [20].

Long cycle (3400 seconds) and short cycle (1300 seconds) are considered during the study. Previous experimental investigations revealed that the adsorption chiller works effectively for relatively higher heat source temperature (above 65 ^{o}C) with short cycle time and for lower heat source temperature (below 65 ^{o}C) with long cycle time. Therefore, for the purpose of this study the short cycle time with heat source temperature at 80 ^{o}C and long cycle time with heat source temperature at 60 ^{o}C are selected [20]. Baseline parameters of the chiller are given in tab. 1 [20].

Table 1. Baseline parameters of the re-heat two-stage chiller

Parameter	Value	Unit
C_{sorb}	924.0	[Jkg^{-1}K^{-1}]
M_{sorb}	16.0	[kg]
hA_{ads}	2497.6	[WK^{-1}]
hA_{des}	2532.5	
hA_{evap}	989.9	
hA_{cond}	2404.3	
hA_{ads}	2497.6	

The following flow rates were recorded during tests in standard operating conditions: hot water: 0.5 kg/s, cooling water: 0.5 kg/s in absorber, and 0.3 kg/s in condenser. The temperatures of cooling and chilled water in standard operating conditions were: 30 ^{o}C and 14 ^{o}C, respectively [20]. A further detailed description of the chiller, including considered operating strategy, can be found elsewhere [20].

The ANFIS model

For the purpose of this paper the experimental results given in [20, 21] were used to derive and validate model parameters. An ANFIS is a fuzzy system whose membership function parameters were tuned using neuro-adaptive learning methods, similar to methods used in training neural networks [22].

The MATLAB® R2018a, with the neuro-fuzzy toolbox is used to develop the model and predict the CC of the considered re-heat two-stage adsorption chiller [22]. The following values: adsorbent mass, M_{sorb}, cycle time, t, hot water temperature, T, adsorbent-to-metal thermal capacitance ratio, C_{sorb}/C_{met}, overall evaporator and sorption element thermal conductance, hA_{evap}, and hA_{sorb}, respectively, are assumed as input parameters. The data are given in tab. 2. The CC of the re-heat two-stage adsorption chiller constitutes the output parameter.

The schematic diagram of the model with all considered inputs and the output is given in fig. 2.

Table 2. The input parameters used in the study

Input parameter	Value
Adsorbent mass, M_{sorb}, [kg]	4.7-80.0
Cycle time, t, [s]	1300, 3400
Hot water temperature, T, [^{o}C]	60, 80
Adsorbent-to-metal thermal capacitance ratio, C_{sorb}/C_{met}, [–]	1, 2.75, 50
Overall evaporator thermal conductance, hA_{evap}, [WK^{-1}]	1000-4000
Overall sorption element thermal conductance, hA_{sord}, [WK^{-1}]	

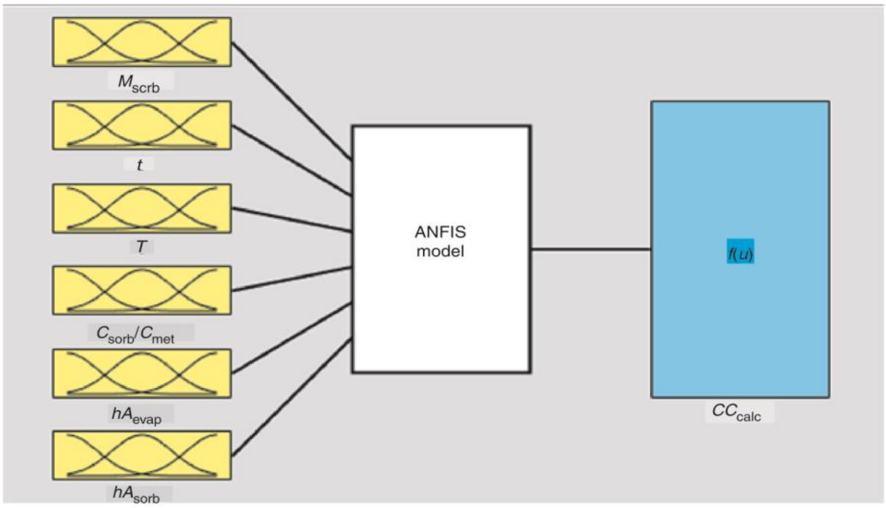

Figure. 2. The schematic diagram of the model

The neuro-fuzzy designer provides two partitioning data techniques for generating the initial fuzzy inference structure (FIS) model: grid partition, which generates a single-output Sugeno-type FIS by using grid partitioning on the data and sub clustering, where an initial model is generated for ANFIS training by first applying subtractive clustering on the data. The subtractive clustering method partitions the data into clusters, and generates an FIS with the minimum number of rules required to distinguish the fuzzy qualities associated with each clusters [22]. For the purpose of this work the sub clustering method, were employed for generating the initial FIS, since a clear idea how many clusters should be for the considered data set in not known. The subtractive clustering method is a fast, one-pass algorithm for estimating the number of clusters and the cluster centers for a set of data [22, 23]. The subclust function finds cluster centers using subtractive clustering method, while the ANFIS function allows tuning Sugeno-type fuzzy inference system using training data [22]. The following parameters were set for this option: range of influence (range of influence of a computed cluster center in each of the data dimensions) = 0.7, squash factor (only find clusters that are far from each other) = 1.8 accept ratio (only accept data points with a strong potential for being cluster centers), reject ratio (reject data points if they do not have a strong potential for being cluster centers) = 0.3. A graphical representation of the initial FIS model structure is given in fig. 3.

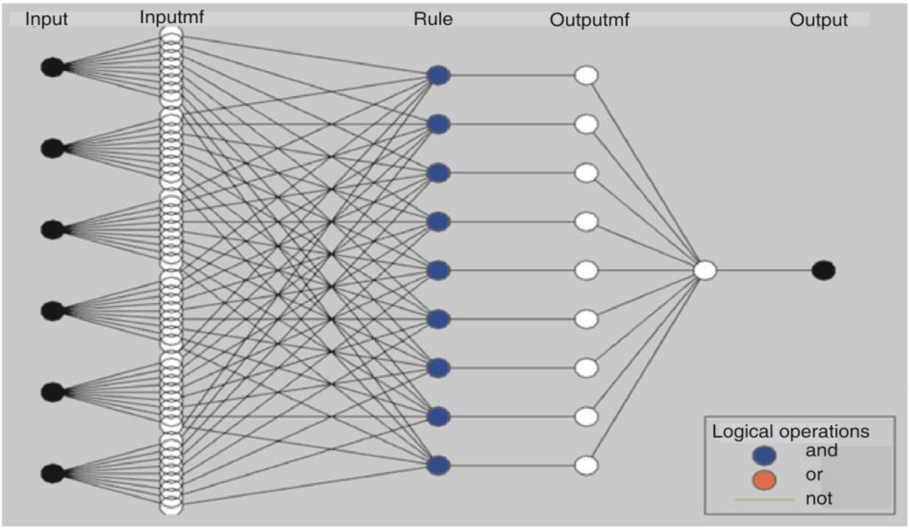

Figure. 3. The ANFIS model structure (*for colour image see journal web site*)

Two optimization methods can be applied for training the membership function parameters to emulate the training data: the conventional backpropagation method, which is considered as a steepest descent method [13, 14, 22] and the hybrid optimization method, which is a combination of least-squares and backpropagation gradient descent method.

In the hybrid method the backpropagation technique is applied for the parameters associated with the input membership functions whereas least squares estimation is used for the parameters associated with the output membership functions [22]. In this work the hybrid optimization method was employed leading to the decrease of training error.

The training the ANFIS model was performed for the following stopping criteria for training: number of training epochs equal to 3000 and the error tolerance is 0.1.

Results and discussion

The testing results of the developed FIS against the training data are given in fig. 4.

Similar comparison for checking data (previously unseen by the ANFIS model) can be found in fig. 5.

From figs. 4 and 5 we can see that both training and checking data against the FIS looks satisfactorily. The calculated data are close to the desired ones. The minimal training and checking RMSE are equal 0.213 and 0.263, respectively.

The comparison between desired and calculated by the model results is given in fig. 6. The relative error is defined by:

$$\delta = 100\frac{CC_\mathrm{d} - CC_\mathrm{calc}}{CC_\mathrm{d}} \tag{1}$$

The data shown in fig. 6 correspond to different input parameters. The calculated results are located within the range of ±10% of relative error, compared to the desired data.

The comparison for checking, *i. e.* new, previously unused independent data is shown in fig. 7. Good accuracy in prediction of CC by the ANFIS model was obtained. The relative error of predictions is also located within the range of ±10%.

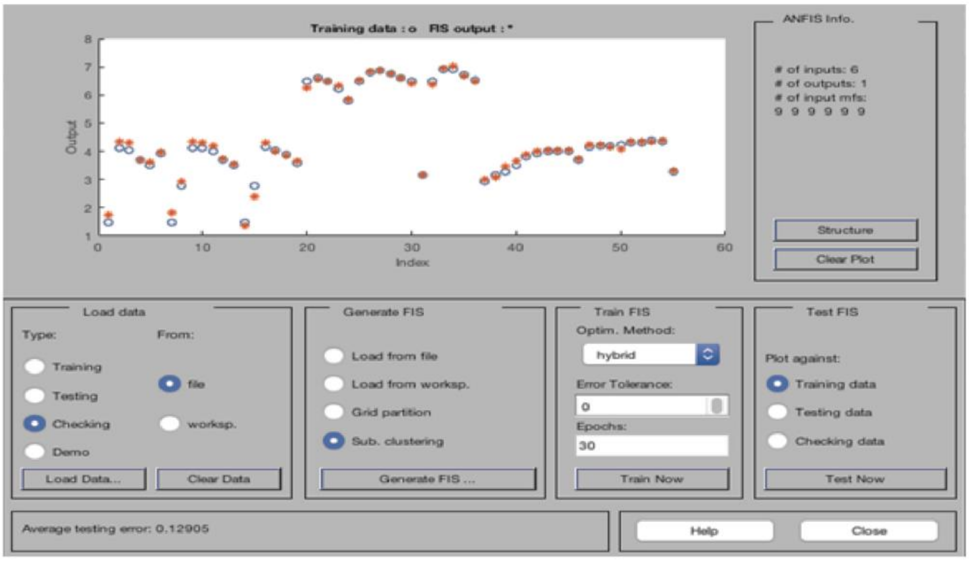

Figure. 4. Training data (the blue points) against FIS output (the red points)
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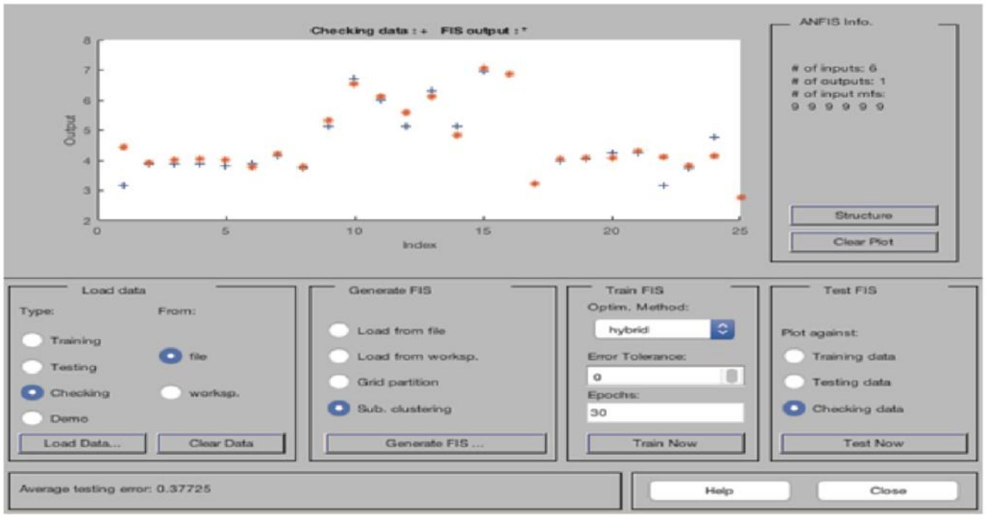

Figure. 5. Checking data (the blue points) against FIS output (the red points)
(*for colour image see journal web site*)

The sources of the reported inaccuracies correspond to the errors of measurements as well as the modeling technique. The reported low discrepancies between calculated and desired results are acceptable and confirm the proposed approach to be a useful method of data handling.

In order to study the influence of a specific operating variable on the CC, other input parameters have to be fixed and keep unchanged during the analysis.

The dependence can be only established for the specific operating conditions. Such undertaking was applied in the next/further parts of the paper.

The effect of adsorbent mass and adsorbent-to-metal thermal capacitance ratio on CC

The influence of adsorbent mass on CC can be found in fig. 8. As adsorbent mass increases from 4.7-32 kg the CC increases due to the increase of bed sorption properties. Higher mass of silica gel allows for higher amount of vapor being sorbed in the porous structure of adsorbent beds. However further increase in adsorbent mass leads to the decrease in CC. The reason is, that other operating parameters including fluid temperatures and flow rates, are fixed, whereas higher amount of silica gel needs more heat input to keep the sorbent in the proper temperature during sorption stage [20, 21]. The CC for shorter cycle (1300 seconds) and higher hot water temperature (80 ^{o}C) are higher than the one for longer cycle (3400 seconds) and lower hot water temperature (60 ^{o}C). The reason is, that the hot water temperature is one of the main factors influencing CC.

Since higher hot water temperatures allows better prepare the adsorption bed for the consecutive adsorption stage the increase in bed temperature also leads to the increase in CC.

The influence of adsorbent-to-metal thermal capacitance ratio C_{sorb}/C_{met} on CC is shown in fig. 9. The results are given for three values: 1.0, 2.75 (base line) and 50 [20]. Maximum CC value equal 7.08 kW was obtained for M_{sorb} = = 40 kg and C_{sorb}/C_{met} = 50.

To keep constant of C_{sorb}/C_{met} ratio for each plot, both the adsorbent and metal masses varied in the same proportions [20]. The CC is sensitive to adsorbent-to-metal thermal capacitance ratio mainly for higher masses of adsorbent. Similar behavior was reported by Khan *et al*. [20].

Since Khan *et al*. [20] have not observed such sensitivity for lower amounts of silica gel the differences in CC depicted in in this region in fig. 9 can be attributed the approximation error of the method.

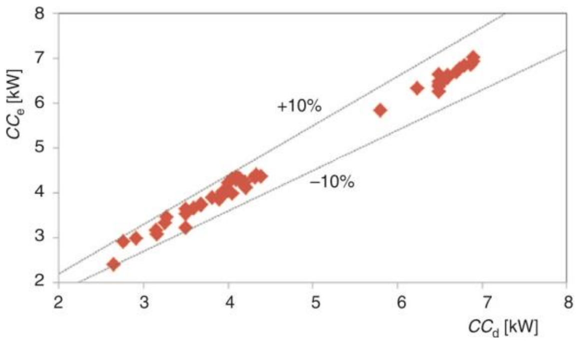

Figure. 6. Comparison of the CC desired and predicted by the model

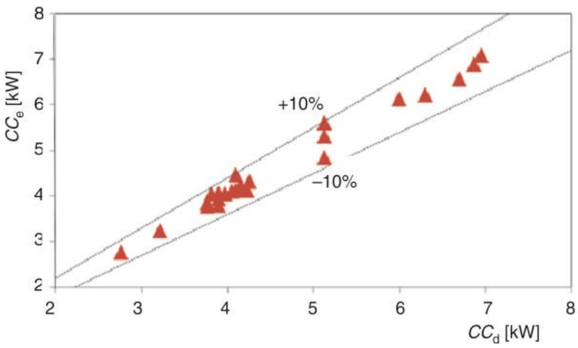

Figure. 7 Comparison of the CC desired and predicted by the ANFIS model, for new, previously unseen data set

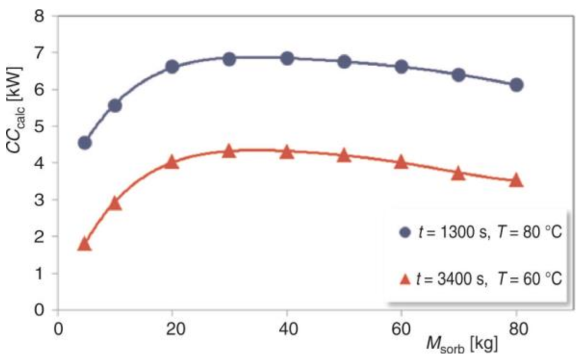

Figure. 8. The influence of adsorbent mass on CC (C_{sorb}/C_{met} = 2.75, hA_{evap} = 989.9 W/K, hA_{sorb} = 2497.6 W/K)

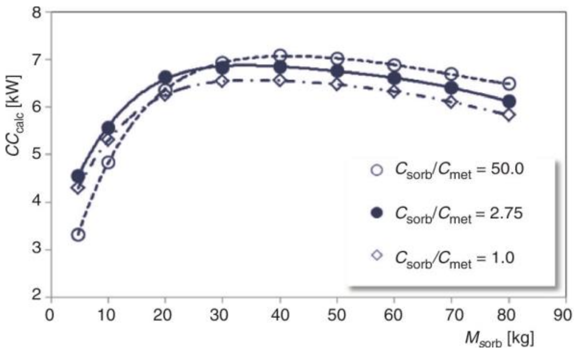

Figure. 9. The effect of adsorbent-to-metal thermal capacitance ratio C_{sorb}/C_{met} on CC (t = 1300 s, T = 80 °C, hA_{evap} = 989.9 W/K, hA_{sorb} = 2497.6 W/K)

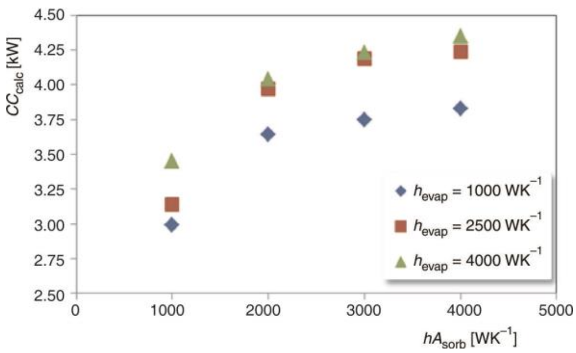

Figure. 10. The effect of sorption element thermal conductance on CC (M_{sorb} = 16 kg, t = 3400 s, T = 60 °C, C_{sorb}/C_{met} = 2.75)

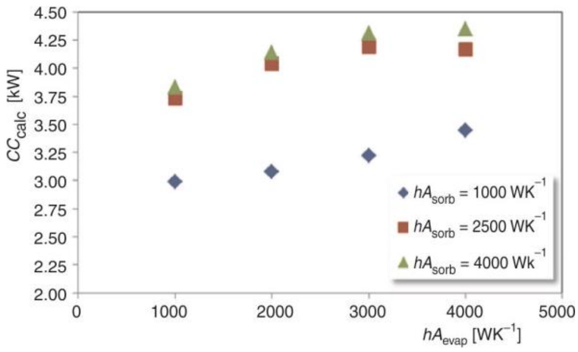

Figure. 11. The effect of evaporator thermal conductance on CC (M_{sorb} = 16 kg, t = 3400 s, T = 60 °C, C_{sorb}/C_{met} = 2.75)

The effect of sorption element and evaporator thermal conductance on CC

The thermal conductance, hA, is determined by multiplying the overall heat transfer coefficient, h, and the effective surface area, A, of the heat exchanger [20].

The influence of thermal conductance of sorption element on CC is depicted in fig. 10. Three data series correspond to different values of thermal conductance of evaporator, namely: 1000, 2500, and 4000 W/K.

The higher sorption element thermal conductance means better heat transfer conditions inside the sorption element and the increase in hA_{sorb} allows for better preparation of the bed for the adsorption process.

This also means higher amount of refrigerant inside the bed and better performance, leading to the increase in CC [20]. The influence of evaporator thermal conductance hA_{evap} on the CC is depicted in fig. 11.

As the hA_{evap} increases the CC also tends to increase. Similar to the hA_{sorb} the increase in hA_{evap} means better heat transfer between chilled water and the vapor produced. Therefore, the improved heat transfer conditions within the evaporator leads to the increase in CC of the re-heat two-stage adsorption chiller.

The performed calculations allows to determine optimal experimental and design parameters. Taking into account the previous described observations and the considered range the input data the highest value of the CC can be reached for the following design and operations inputs: M_{sorb} = 40 kg, t = 1300 s, T = 80 °C, C_{sorb}/C_{met} = 50, hA_{sorb} = 4000 W/K, hA_{evap} = 4000 W/K, fig. 12.

The maximum CC value of the considered re-heat two-stage adsorption chiller is equal 21.7 kW.

Conclusions

The paper deals with an innovative design in cooling production, a re-heat two-stage adsorption chiller. The results of simulations of the chiller behavior using novel approach with AI methods are discussed in this paper. The neuro-adaptive fuzzy-inference system approach was employed in the paper.

The maximum relative error of the developed model is lower than 10 %.

The highest value of CC of the considered re-heat two-stage adsorption chiller is equal 21.7 kW and can be achieved for the following design and operational parameters: M_{sorb} = 40 kg, t = 1300 s, T = 80 °C, C_{sorb}/C_{met} = 50, hA_{sorb} = 4000 W/K, hA_{evap} = 4000 W/K. The developed model constitutes an easy-to-use and powerful optimization tool which allows estimating the CC of the re-heat two-stage adsorption chiller.

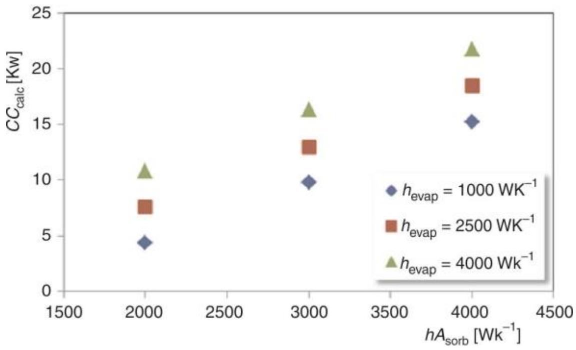

Figure. 12. The effect of sorption element thermal conductance on CC for optimum design and operational parameters (M_{sorb} = 40 kg, t = 1300 s, T = 80 °C, C_{sorb}/C_{met} = 50)

Acknowledgment

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Nomenclature

A – area, [m^2]
C – specific heat capacity, [Jkg^{-1}K^{-1}]
h – heat transfer coefficient, [Wm^{-2}K^{-1}]
M – mass, [kg]
t – cycle time, [s]
T – hot water temperature, [°C]

Greek symbol

δ – relative error, [%]

Subscripts

ads – adsorber
calc – calculated
cond – condenser
d – desired
des – desorber
evap – evaporator
met – metal
sorb – sorbent

Acronyms

AI – artificial intelligence
ANFIS – adaptive neuro-fuzzy inference system
CC – cooling capacity
FIS – fuzzy inference structure
SCP – specific cooling power

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