SUSTAINABLE WORKING FLUIDS SELECTION FOR THE LOW TEMPERATURE ORGANIC RANKINE CYCLE

S. N. HADDAD, smr.haddad@gmail.com George Brown College, Toronto, Canada

S.ARTEMENKO, sergei.artemenko@gmail.com Odessa State Academy of Refrigeration, UA

D. NIKITIN, dnn@utecon.com Odessa State Academy of Refrigeration, UA

ABSTRACT

A general approach to the working fluid selection for the organic Rankine cycle that meets a sustainable development criterion has been developed. The various configurations of the Rankine cycle based on the organic working fluids were considered. The direct assessment of the efficiency criteria for the Rankine cycle via artificial neural networks (ANN) was proposed. To create ANN the critical parameters of substance and normal boiling temperature as input were chosen. The forecast of efficiency criteria for the Rankine cycle as output parameters which describe the coefficient of performance with high accuracy and without thermodynamic property calculations were given.

Keywords: Working Fluids; Organic Rankine Cycle; Coefficient of Performance; Artificial Neural Networks.

I. INTRODUCTION

The transformation of heat into mechanical work is based on the application of Rankine cycle. Water is the basic working fluid for such cycles where high temperature sources exist, Low temperature sources of heat (i.e. industrial thermal wastes, geothermal sources, solar ponds, etc.) can be transformed into work if an organic fluid with a lower normal boiling temperature in compare to water vapor will be used. The Rankine cycles working on organic substances, have received the name of Organic Rankine Cycle – ORC and have found wide application as new technologies to utilize the waste heat of various industrial processes and in agriculture (for example, at condensation of smoke gases, a fermentation, recycling of exhaust gases of internal combustion engines), in cogeneration systems, and also many other applications [1], [15] – [26].

The key point of ORC is the selection of the working fluid, where the its physical and chemical characteristics determine the power efficiency of system in whole. To utilize low temperature heat source, working fluids of ORC should possess normal boiling temperature below 350 K, practically at the vertical right boundary curve in the temperature – entropy diagram, with high heat of evaporation, high density and comprehensible operational qualities. Besides, several restrictions associated with

ecological and technological standards and safety requirements are imposed on the selection of the working fluid. However, a working fluid that would satisfy all design conditions and not having disadvantages, does not exist. Therefore it is meaningful to look at some compromise proposals to find the ORC working fluids possessing the maximum advantages.

The objective of the present work is to develop a general approach to select the working fluid for the Organic Rankine Cycle.

II. SUSTAINABLE DEVELOPMENT CRITERIA OF THE CHOICE OF ORC WORKING FLUIDS SELECTION

The concept of sustainable development considers an integrated solution of the ecological, economic, social and cultural problems arising from the design of technical systems. The problem of perspective working media selection for ORC is closely connected with the development of the modern technologies constructed on the concept of sustainable development, combining balance between high power parameters and ecological safety. To solve this problem, achievements of information technologies and the molecular theory, technical experience and experimental data [2] - [4] are used.

There is a multitude of efficiency criteria and the achievement of the extreme for each of them is the ultimate goal of the design. Usually a compromise among three basic criteria – energy, economic and ecological, is been attempted. The generalized criterion of efficiency for all system as a whole is represented by a vector **K**, which includes local criteria K_i that reflect the set of requirements to ORC working fluids by the consumer.

Achievement of the optimum decision corresponds to the compromise between various criteria and displays the quality of engineering decisions. Criteria of sustainable development cannot be formulated on a strict mathematical basis and always have subjective character. The several approaches for finding the compromise between local criteria and constructions of generalized criterion function were offered. For example, in traditional thermodynamics analysis, the concept exergy or exergy-ecological costs is introduced for monetary and power values. Additive convolution of power and ecological parameters of efficiency has been offered for the analysis of refrigerating systems in criterion TEWI [5]. A weak point of such approaches is the implicit assumption about conformity of the economic (ecological) and power objectives that contradicts a real situation.

Finding the compromise actually is a difficult decision-making for multicriteria problems and cannot be formalized. There are some ways of transformation of vector criterion in scalar which were discussed earlier [4], [6].

Sustainable decision is defined by the Bellman and Zadeh model [7] as the intersection of all local fuzzy criteria and is represented by its membership function $\mu_i(X)$ as follows:

$$\mu_C(X) = \mu_1(X) \cap \mu_2(X) \ldots \cap \mu_n(X)), \; i = 1,2,\ldots, n; \quad X \in X_P \tag{1}$$

The membership function of the objectives and constraints can be chosen linear or nonlinear depending on the context of problem. One of possible fuzzy convolution schemes is presented below.

Initial approximation $\boldsymbol{X}$-vector is chosen. Maximum (minimum) values for each criterion K_i are established via scalar maximization (minimization). Results are denoted as "ideal" points $\{ X_j^0 \; , j = 1 \ldots m \}$.

Maximum and Minimum bonds for criteria are defined:

$$K_i^{min} = \min_j K_j(X_j^0) = K_i(X_i^0), \; i = 1 \ldots n; \; K_i^{max} = \max_j K_j(X_j^0), \; i = 1 \ldots n. \tag{2}$$

The membership functions are assumed for all fuzzy goals as follows:

$$\mu_{Ki}(X) = \begin{cases} 0, & if \;\; K_i(X) > K_i^{max} \\ \dfrac{K_i^{max} - K_i}{K_i^{max} - K_i^{min}} & if \;\; K_i^{min} < K_i \le K_i^{max}, \\ 1, & if \;\; K_i(X) \le K_i^{min} \end{cases} \tag{3}$$

A final decision is determined as the intersection of all fuzzy criteria represented by its membership functions. This problems is reduced to the standard nonlinear programming problems: to find such values $\boldsymbol{X}$ and λ that maximizes λ subject to

$$\lambda \le \mu_i(X), \quad i = 1, 2, \ldots, n; \tag{4}$$

The solution yielded as a result of intersection of accessory functions to all fuzzy criteria with restrictions, is formally considered as the best approach criterion of sustainable development for the given system.

III. CONFIGURATIONS LOW- TEMPERATURE ORC

The selection of working fluid for an ORC had three possible configurations of cycles, which have different form of saturation curves (dark blue lines in electronic on-line versions) in T–S diagram (fig. 1 – 3)

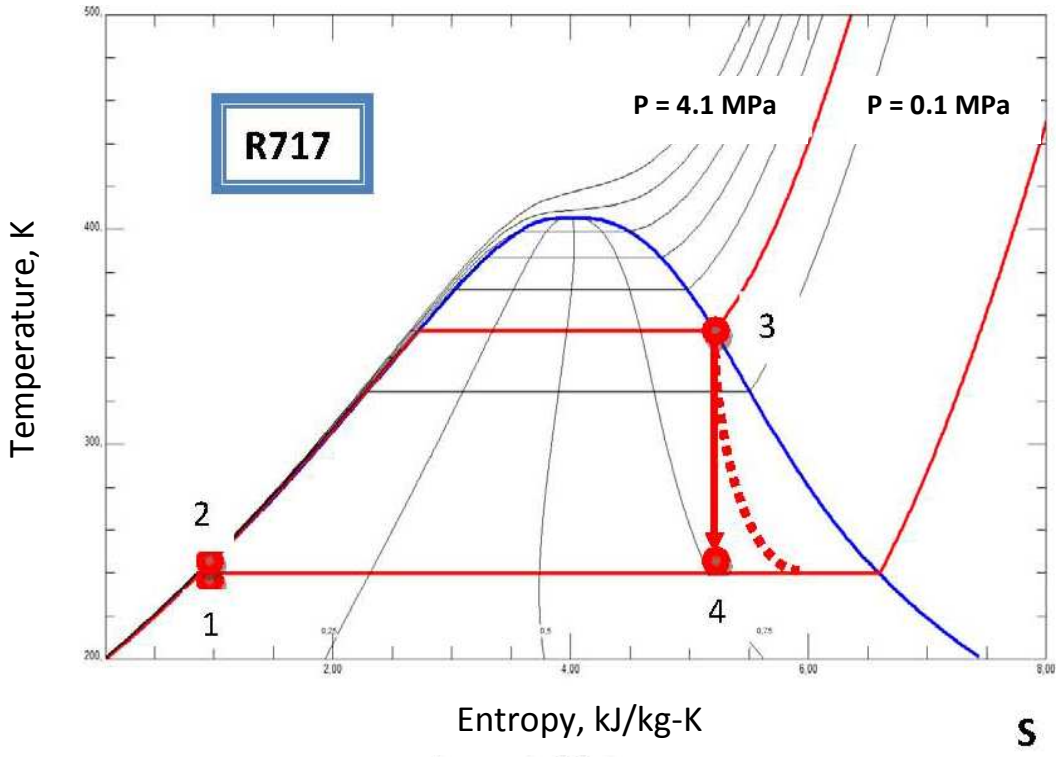

Figure1. Configuration (A) for Ammonia working fluid in T – S diagram

For a configuration A (fig. 1) the pressure of the working fluid is raised of result an adiabatic process in the pump from a condition of the saturated liquid in the condenser (point 1) to the evaporator in which the pressure is below the critical value(at point 2). Further the liquid is heated in the evaporator at constant pressure to a condition of saturated vapor (at point 3). In the turbine, as result of reversible adiabatic expansions of the working fluid, a work is done (process 3 – 4). Condition 4 settles down in two-phase area. The real process of adiabatic expansion is irreversible and displaces the final state 4 to the right (as shown in figure 1) The cycle is completed when the stream of the working fluid from a state 4 returns to the initial condition 1 at constant pressure process, giving heat to a cold source.

The configuration in (fig. 2) is similar to the configuration in figure 1. The main difference from previous configuration is that saturated vapor is heated to point 3 such that after expansion in the turbine it will stay in the superheated region (state 4).

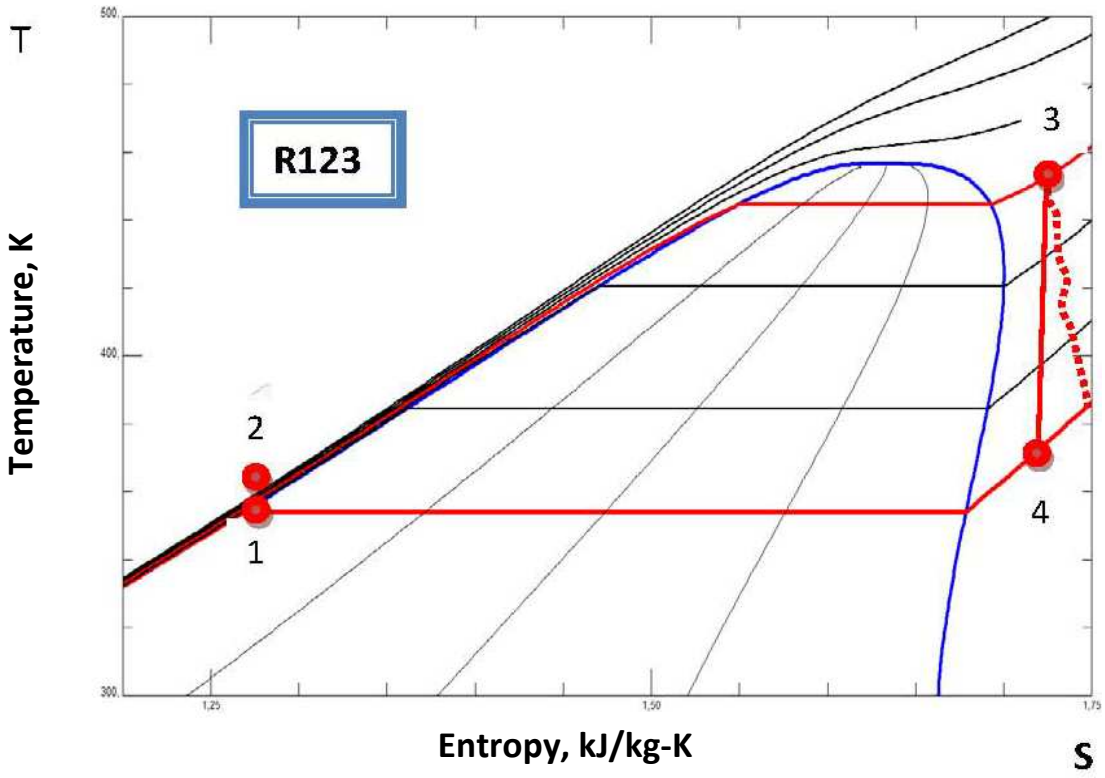

Figure2. Configuration (B) with superheated vapor for R 123 in T – S diagram.

The configuration in (fig. 3) is the same as in A. The main difference is in the form of the right saturation curve along which the thermal capacity changes its sign. As a result of the adiabatic expansion in the turbine the final state of the fluid will be in the super heated region of the T-s diagram and not in the two phase region.

The modeling of characteristics of the ORC is based on the First and second laws of thermodynamics. The equations describing processes in a cycle are well-known and are summarized below.

Work adiabatic compression (expansion) in the pump 1 – 2 (turbine 3 – 4) in a reversible process is equal to:

$$L_{12} = \dot{m} v_1 (P_2 - P_1)$$

(5)

$$L_{34} = \dot{m} T_0 (h_3 - h_4),$$

(6)

In irreversible process:

$$L_{12}^{*} = L_{12} - \dot{m} T_0 (s_2 - s_1),$$

(7)

$$L_{34}^{*} = L_{34} - \dot{m} T_0 (s_4 - s_3).$$

(8)

Where,

m – the mass flow rate of the working fluid, v, P, h, s are volume, pressure, enthalpy, and entropy, respectively. T_0 is the ambient temperature.

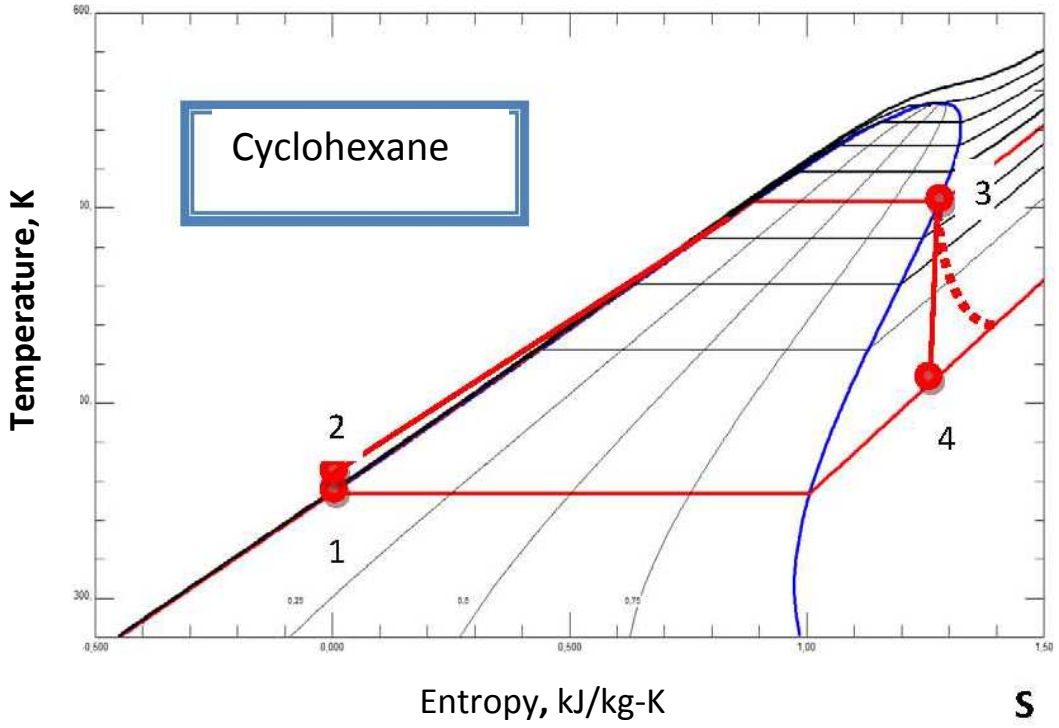

Figure3. Configuration (C) for cyclohexane in T – S diagram

Heat addition (removal) to a working fluid at constant pressure in the evaporator (condenser) is defined by:

$$Q_{23} = \dot{m}(h_3 - h_2), \tag{9}$$

$$Q_{41} = \dot{m}(h_4 - h_1). \tag{10}$$

The coefficient of performance COP, a criterion of power efficiency of the Rankine cycle is:

$$COP = \frac{L_{12} - L_{34}}{Q_{23}}.$$

(11)

Therefore, the determination of cycle efficiency requires the knowledge of the thermodynamic properties of working substance in a wide range of change of state properties. Unfortunately, a substance for which there is full information necessary for calculation of power cycle efficiency of working fluids is limited. Development of the approaches combining the previous knowledge of known thermodynamic properties and criteria of efficiency of systems of transformation of energy with methods of an artificial intellect which are the tool for reception of the new information in conditions of uncertainty therefore is of interest. One of such approaches to forecasting characteristics of not studied working bodies is application of artificial neural networks.

IV. ARTIFICIAL NEURAL NETWORKS FOR THE ESTIMATION OF ENERGY EFFICIENCY ORC

The thermodynamic behavior of all one component substances in gas and liquid phases has identical topological structure similar to the cubic equations of a state. The reliable quantitative description of a thermodynamic surface can be reached within the limits of the theory of similarity when the number of dimensionless parameters is enough. Unfortunately, theoretically it is impossible to establish number of respective conditions which could provide concurrence of thermodynamic surfaces for various substances in a wide range of parameters of a state. In that case, when processes occur in a vicinity of boundary curves, the good description of thermodynamic properties is reached in three parameter approach of the similarity theory.

From this point of view, critical temperature – T_C and pressure – P_C together with normal boiling temperature – T_B are the most rational values which provide correct description of thermodynamic surfaces near the saturation curve.

Artificial neural networks represent the mathematical tool which during training allows establishing dependences between entrance data and target characteristics of any degree of complexity. The purpose of training is to find factors of communications between neurons, which define abilities of a neural network to allocation of the latent dependences between entrance and target values. After training, the network becomes capable of forecasting new data on the basis of the limited sample of known interrelations between entrance and target values. In this case, we aspire on the basis of the known information on the entrance given T_C, P_C and T_B for restricted set of known substances which are connected by complex relationships with target value – COP, to predict energy characteristics of the Rankine cycle for not studied substances only on the basis of known data about critical parameters and normal boiling temperature.

In table 1 temperature borders (T_3, T_4) and a range of admissible pressure (Pmin, Pmax) which characterize the operating conditions for ORC are listed.

Table1. Comparison of conversion factors for the organic Rankine cycle (COP) [8] with calculations based on artificial neural networks

Refrigerant	Cycle Type	T_C, ^0C	P_C, MPa	T_B, ^0C	T_3, ^0C	T_4, ^0C	P_{min}, MPa	P_{max}, MPa	COP ,%, [8]	COP, %,ANN	Δ, %
R32	A	78,11	57,83	-51,7	31,36	30,00	19,31	20,00	0,36	0,38	-4,51
R32	B	78,11	57,83	-51,7	100,00	97,75	19,31	20,00	0,42	0,44	-4,33
R125	A	66,18	36,3	-48,1	40,06	30,00	15,64	20,00	2,32	2,38	-2,38
R125	B	66,18	36,3	-48,1	100,00	91,92	15,64	20,00	2,36	2,36	0,08
RE125	A	81,34	33,51	-35	100,00	79,04	10,11	20,00	5,77	6,02	-4,27
R134a	A	101,03	40,56	-26,1	67,75	30,00	7,72	20,00	7,74	7,73	0,12
RE134	C	147,1	42,28	5,5	100,00	41,04	2,50	16,66	12,56	12,48	0,66
R143a	A	72,73	37,64	-47,2	43,59	30,00	14,40	20,00	3,14	3,08	1,97
R143a	B	72,73	37,64	-47,2	100,00	87,37	14,40	20,00	3,31	2,98	10,02
R152a	A	113,5	44,95	-24	72,59	30,00	6,89	20,00	8,82	8,78	0,47
R152a	B	113,5	44,95	-24	100,00	53,84	6,89	20,00	9,22	9,27	-0,59
RE170	A	126,85	52,4	-24,8	75,10	30,00	6,73	20,00	9,38	9,29	0,97
RE170	B	126,85	52,4	-24,8	100,00	53,03	6,73	20,00	9,68	9,84	-1,63
R218	C	71,89	26,8	-36,8	58,99	33,68	10,04	20,00	5,22	5,22	0,03
R227ea	C	101,74	29,29	-16,4	83,88	44,19	5,33	20,00	9,2	9,22	-0,22
R236ea	C	139,22	34,12	6,19	100,00	53,92	2,44	15,74	12,02	12,16	-1,15
R245ca	C	174,42	39,25	25,1	100,00	53,75	1,23	9,34	12,79	12,96	-1,32
R236fa	C	125,55	32	-1,4	100,00	48,61	3,24	19,35	11,63	11,55	0,68
R245fa	C	154,05	36,4	15,1	100,00	50,70	1,80	12,67	12,52	12,51	0,08
RE245mc	C	133,68	28,87	5,59	100,00	54,50	2,42	14,88	11,84	11,82	0,19
RC270	A	124,65	54,9	-31,5	100,00	41,63	8,23	20,00	8,86	8,62	2,72

R290	A	96,65	42,5	-42,1	57,14	30,00	10,79	20,00	5,91	5,91	-0,06
R290	B	96,65	42,5	-42,1	100,00	76,02	10,79	20,00	6,11	6,18	-1,19
RC318	C	115,23	27,78	-6	98,93	54,72	3,68	20,00	10,97	10,69	2,57
RE347mcc	C	164,55	24,76	34,23	100,00	56,38	3,68	20,00	11,72	11,22	4,28
R600	C	152,05	38	-0,5	100,00	48,43	2,85	15,29	12,58	12,53	0,39
R600a	C	135,05	36,5	-11,7	100,00	45,33	4,04	19,98	12,12	12,11	0,05
R601	C	196,5	33,7	27,8	100,00	57,74	0,83	5,96	12,91	12,87	0,34
R601a	C	187,75	33,86	36,1	100,00	58,47	1,10	7,22	12,75	12,75	-0,03
R1270	A	92,42	46,65	-47,7	48,54	30,00	13,09	20,00	4,28	4,28	-0,06
R1270	B	92,42	46,65	-47,7	100,00	81,28	13,09	20,00	4,53	4,16	8,17
C5F12	C	148,85	20,4	29	100,00	72,76	1,04	7,66	10,49	10,49	0,00
CF3I	A	123,29	39,53	-21,9	85,24	30,00	5,65	20,00	10,63	10,68	-0,46
CF3I	B	123,29	39,53	-21,9	100,00	39,60	5,65	20,00	10,93	10,93	-0,02
n-hexane	C	234,67	30,1	341,86	100,00	61,89	0,25	2,48	13	13	0,00

The sequence of construction of an artificial neural network included the following sequence f actions: a choice of initial data for training; a choice of architecture of a network; dialogue selection of characteristics of a network; experimental selection parameters of training; process of training; check of adequacy of training (validation); and forecasting. Calculations are done in Matlab Neural Network Toolbox environment [9]. Algorithm of back propagation was used for training a neural network. Exit values in the initial sample were calculated for various configurations of cycles based on thermodynamic properties as reported in [8]. As entrance values the given Tc, Pc and To are used. For training, various architecture of neural networks, with different quantity neurons and transitive functions on the first and second layers, was considered. The third layer of a network always contains one neuron with linear active function.

For configuration A two latent layers were used. The first contained two neurons and the second – one. As transfer functions hyperbolic tangent was used. As training sample data for working fluids R125, R143a, R32 and R1270 were used. Testing was done for R152a, CF3I, and RE170. Check of adequacy was done for R290 and R134a. Results are listed in table 1.

For configuration B two latent layers were used. The first contained five neurons and the second – one. As transfer functions hyperbolic tangent was used. As training

sample data for working fluids R125, R143a, R152a and RC270were used. Testing was done for RE125, R1270 CF3I and RE170. Check for adequacy was done for R32 and R290. Results are listed in tab. 1.

Construction of an artificial neural network for a configuration C coincides with architecture of a network for a configuration B. Training sample included the following working fluids: R218, R236fa, RE245mc, C5F12, R600, R601a, n-Hexane.

Testing was done on the set of substances: R227ea, R236ea, RE134, R245fa RE347mcc, R601, and final verification accordingly for RC318, R600a and R245ca. Results of reproduction of characteristics of the Rankine cycle are listed in Table 1. Deviations of "experimental" values of COP [8] from calculated by means of the trained artificial neural network (Fig.4) are within the limits of an error of calculations by means of the multi-constant equations of state [10] – [14]. Appreciable deviations in values of a relative error (more than 5 %) are observed for low values COP that has no basic value as a choice of working fluids with the maximal power efficiency.

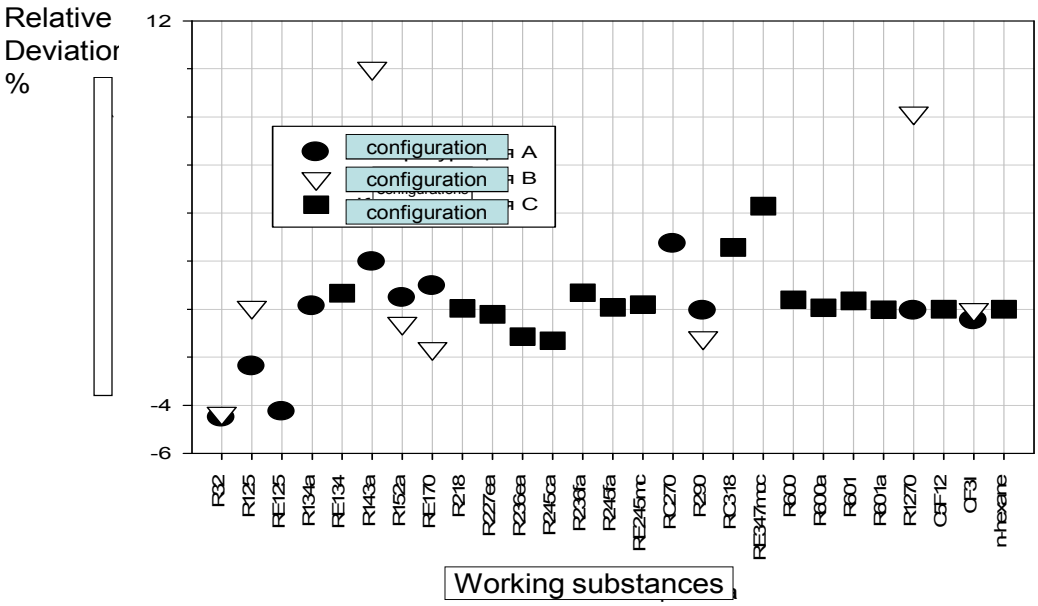

Figure 4. Accuracy of neural network predictions of the COP for various configurations ORC compared with the thermodynamic data

CONCLUSION

In this work, criteria of sustainable development for technologies of transformation low temperature sources of heat into work on the basis of the Rankine cycle using organic working fluids were developed. For search of new working fluids, which have no information on thermodynamic behavior, ANN approach is offered to forecast energy efficiency of Rankine cycles. On the basis of the limited data about

critical parameters and normal boiling temperature of substances for various configurations of cycles, the values of COP are determined without the calculation of thermodynamic processes.

Construction of ANN correlations between information characteristics of working fluids, in which the basic points of substance are related to the criteria of efficiency of Rankine cycle, dives the rise for the need of search of ORC technologies, satisfying criteria of steady development. In subsequent works on this topic, new classes of working fluids for ORC systems for which there are no data about thermodynamic properties are considered, and fuzzy criteria of sustainable development for a choice of perspective substances are compared.

ACKNOWLEDGEMENT: The authors would like to acknowledge the Odessa State Academy of Refrigeration in the Ukraine to complete this work Also we thank Professor Victor Mazur for helpful discussions and assistance.

REFERENCES

1. **Quoilin, S., Lemort, V., (2009),** "Technological and Economical Survey of Organic Rankine Cycle Systems", The 5th European Conference on Economics and Management of Energy in Industry, Algarve, Portugal.

2. **Joback, K.G., Stephanopoulos, G., (1989),** "Designing Molecules Possessing Desired Physical Property Values, Proceedings of the Foundations of Computer-Aided Process Design (FOCAPD)", Snowmass, CO, July 12-14 - 363 – 387.

3. **Duvedi, A., Achenie, E., (1996),** "Designing Environmentally Safe Refrigerants Using Mathematical Programming", Chemical Engineering Science, 51, No.15. 3727 - 3739.

4. **Mazur, V., (2003),** "Optimum Refrigerant Selection for Low Temperature Engineering", Low Temperature and Cryogenic Refrigeration, Kluwer Academic Publishers, 101.

5. The refrigeration sector's commitment to sustainable development and mitigation of climate change, / www.iifiir.org

6. **Artemenko, S., Masur, V., (2009),** "The Choice of working fluids in energy transforming systems on the basis of fuzzy multicriteria analysis", East-European Journal of Modern Technologies, 4/11, (40), 41-47.

7. **Bellman, R., Zadeh, L., (1970),** "Decision-making in a fuzzy environment", Management Science, 17, 141–164 8.

8. **Saleh, B., Koglbauer, G., Wendland, M. J., (2007),** "Working fluids for low temperature Organic Rankineycles", Energy, 32, 1210–1221.

9. **MATLAB 7.9,** / mathworks.com/products/matlab

10. **Mueller, A., Winkelmann, J., Fischer, J., (1996),** "BACKONE. Family of equations of state, 1, Nonpolar and polar pure fluids", AIChE J, 42, 1116–26.

11. **Weingerl, U., Wendland, M., Fische,r J., Mueller, A., Winkelmann, J., (2001),** "BACKONE**.** Family of equations of state, 2, Nonpolar and polar fluid mixtures", AIChE J, 47, 705–717.12.

12. **Saleh, B., Weinger,l U., Wendland, M., (2001),** " Description of the thermodynamic properties of natural refrigerants with BACKONE equations", In Proceedings of the IIR conference on thermophysical properties and transfer processes of new refrigerants, October 3–5; Paderborn, Germany, 31–38.

13. **Wendland, M., Saleh, B., Fischer, J., (2004),** "Accurate thermodynamic properties from the BACKONE equation for the processing of natural gas", Energy Fuels, 18, 938–951.

14. **Saleh, B., Wendland, M., (2006),** "Screening of pure fluids as alternative refrigerants", International Journal of Refrigeration, 29, 260–269.

15. **Wei, D., Lu, X., Lu, Z., Gu, J., (2007),** "Performance analysis and optimization of Organic Rankine Cycle (ORC) for waste heat recovery", Energy Conversion and Management, 48, 1113–1119.

16. **Borsukiewcz-Gozdur, A., Nowak, W., (2007),** "Comparative analysis of natural and synthetic refrigerants in application to low temperature Clausius–Rankine cycle", Energy, 32, 344–352.

17. **Donghong, Wei., Xuesheng, Lu., Zhen, Lu., Jianming, Gu., (2007),** " Performance analysis and optimization of organic Rankine cycle (ORC) for waste heat recovery" , Energy Conversion and Management, 4, 1113–1119.

18. **Nowak, W., Borsukiewicz-Gozdur, A., Stachel, A.A., (2008),**" Using the low-temperature Clausius–Rankine cycle to cool technical equipment", Applied Energy, 85, 582–588.

19. **Hung, T.C., (2001),** "Waste heat recovery of organic Rankine cycle using dry fluids", Energy Conversion and Management, 42, 539–553.

20. **Liu, B.T., Chien, K.H., Wang, C.C., (2004),** "Effect of working fluids on organic Rankine cycle for waste heat recovery", Energy, 29, 1207–1217.

21. **Mago, P.J., Chamra, L.M., Srinivasan, K., Somayaji, C., (2008),** "An examination of regenerative organic Rankine cycles using dry fluids", Applied Thermal Engineering, 28, 998–1007.

22. **Tchanche, B., Papadakis, G., Lambrinos, G., Frangoudakis, A., (2008),** "Effects of regeneration on low-temperature solar organic Rankine cycles", In Proceedings of Eurosun Conference, Lisbon.

23. **Tchanche, B.F., Papadakis, G., Lambrinos, G., Frangoudakis, A., (2008**), "Criteria for working fluids selection in low-temperature solar organic Rankine cycles", In Proceedings of Eurosun Conference, Lisbon.

24. **Maizza, V., Maizza, A., (1996),** "Working fluids in non-steady flows for waste energy recovery systems", Applied Thermal Energy, 7, 579–590.

25. **Badr, O., Probert, S.D., O'Callaghan, P.W., (1985),** "Selecting a working fluid for a Rankine cycle engine", Applied Energy, 21, 1–42.

26. **Hettiarachchi, H.D.M., Golubovic, M., Worek, W.M., Ikegami, Y., (2007),** "Optimum design criteria for an organic Rankine cycle using low-temperature geothermal heat sources", Energy, 32, 1698–1706.