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AI tool for automatic synthesis of CHP systems

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Inside the EU countries significant investments are expected in both the electricity production and energy transfers within the next 15 years. Such investments will need the precise decision-making processes, supported with very versatile engineering tools. The major objective of this paper is to propose an application of a new methodology to design power systems in a fully automatic way. The proposed methodology utilizes such artificial intelligence tools like genetic algorithms and expert systems.

Keywords: genetic algorithms, expert systems, combined heat and power (CHP), power plant

1. Introduction

Electric power installed in Polish power stations amounts now to 34.5 GW. It is also estimated that demand for the electric power fluctuates from 14.7 GW in summer season to 23.2 GW in peak season during winter. It means that the energy sector in Poland still possesses around 30% of electric power surplus. Simultaneously, it should not be forgotten that 60% of the installed electric power consists of 30 years old power units. Operational use of those units can easily be impeded due to wear and tear. This results in continuous decrease of the energy efficiency of Polish electric power stations. The difference between the energy efficiency of the best electric power stations in Poland and in leading EU countries increased from 4 points in 1985–93 to 8–9 points in 1999. This means that Polish energy sector, although still having the electric power surplus, requires urgent modifications and investments. It is expected that around 2.9 GW of electric power plants will be closed down in Poland by the year 2010 because of their age. Due to the same reason additional 4.3 GW will be shut down by the year 2011–2015 and next 2.8 GW by the year 2020.

The above process of closing down of worn out power units in Poland may even be intensified because of Directive no 2001/80/WE signed on October 23, 2001, with respect to limitation of combustion gases emission. Acceptance by EU countries of Kyoto Protocol should also stimulate some improvements in energy efficiency of power units as the quickest way of CO_2 emission reduction.

It is also commonly accepted that inside the whole EU within the next 15 years some significant investments are expected in both the electricity production as well as in energy transfers. This is estimated roughly at 300GW of newly built power stations worth almost €250 $\cdot 10^9$. Polish energy sector will require investments estimated at €3.1–3.9 $\times 10^9$.

Such investments will need the precise decision-making processes, supported with very versatile engineering tools. To make any analysis required by a designing process fairly general, the type and structure of the power plant has to be decided. This absolutely fundamental decision, fraught with consequences, is equally essential for huge system power stations as well as for small units of distributed electricity generation. All decisions made have to take into account demands for energy of all kinds as well as the local natural resources with special emphasis on the fuels. Coupling element of those two is just a power plant (i.e. electric power station, combined heat and power (CHP), trigeneration unit, etc.). Its detailed project always refers to the type and structure of the plant and to series of assumptions regarding technical data like level of pressures and temperatures in the cycle and so on.

The above crucial decisions are practically based on the former designers' experience only. However, it seems to be reasonable nowadays to utilize within the decision-making process some advanced engineering tools like artificial intelligence.

The major objective of this paper is to propose an application of a new methodology to design power systems taking a combined cycle power plant as an example. This methodology follows an idea published by Melli and Sciubba [8] and utilizes the current artificial intelligence tools like genetic (evolutionary) algorithms and expert systems, with possible future extension with such tools like artificial neural networks or fuzzy logic. [1, 2, 4, 5, 9–12].

This paper opens a series of publications in which application of the AI tools to conceptual synthesis of power generation systems is discussed. The current contribution is devoted mainly to the methodology, although some preliminary numerical tests are also included. Proposed methodology consists of searching for the best configuration (according to adopted objective function) using a genetic algorithm. Following works will be submitted to conferences (or journals) in near future, and will essentially present computational aspects of the proposed approach as well as detailed results of the computer simulations.

2. Proposed approach to power plant synthesis

As already mentioned proposed methodology consists of fully automatic conceptual synthesis of the power plant structure. This structure is composed from basic energy devices like compressor, expander, steam turbine, combustion chamber, heat exchanger, fluidized bed, mixer, etc. Connections of those devices are specified in so-called connectivity matrix. This is rectangular matrix in which its rows represent all input flows while its columns represent all output flows associated with the particular devices. Entry of a representative coefficient c_{ij} can take only value 1 (meaning input i is the same as output number j) or 0 (meaning no connection between ith input and jth output). Changing those coefficients one can easily modify the structure of the plant. Simplicity of such modifications creates favorable conditions for systematic search for a new structure.

It should also be noted that main steps of the designing process of the combined cycle power plant is always associated with optimization which should result in a selection of the best solution (i.e. one of the UNIDO — United Nations Industrial Development Organization, economic criteria as an objective function [3]). Hence, it is natural that proposed methodology eventually leads to developing of the engineering software containing the iterative loop shown in Fig. 1. Optimization, driven by genetic algorithm [1, 5, 10], searches for the best solution (individual) among feasible structures of the power plant (i.e. chromosomes). As already discussed earlier in this section, this is done by means of proposing successive structures of the power plant defining so-called connectivity matrices made of binary elements. At this level considered the elements and the structure itself are also verified according to previously defined knowledge base system (by means of such logical operations as: deduction, induction, decision tree scanning, etc.).

For every structure proposed by the optimization algorithm and verified by the knowledge base system the fitness function has to be evaluated. This is done by means of the numerical model of the analyzed structure. To carry out such calculations some thermodynamic parameters like temperatures, pressures, mass flow rates etc. have to be either assumed making use of the expert system or calculated from appropriate equations. Once the fitness function is calculated, the new feasible structure can be analyzed.

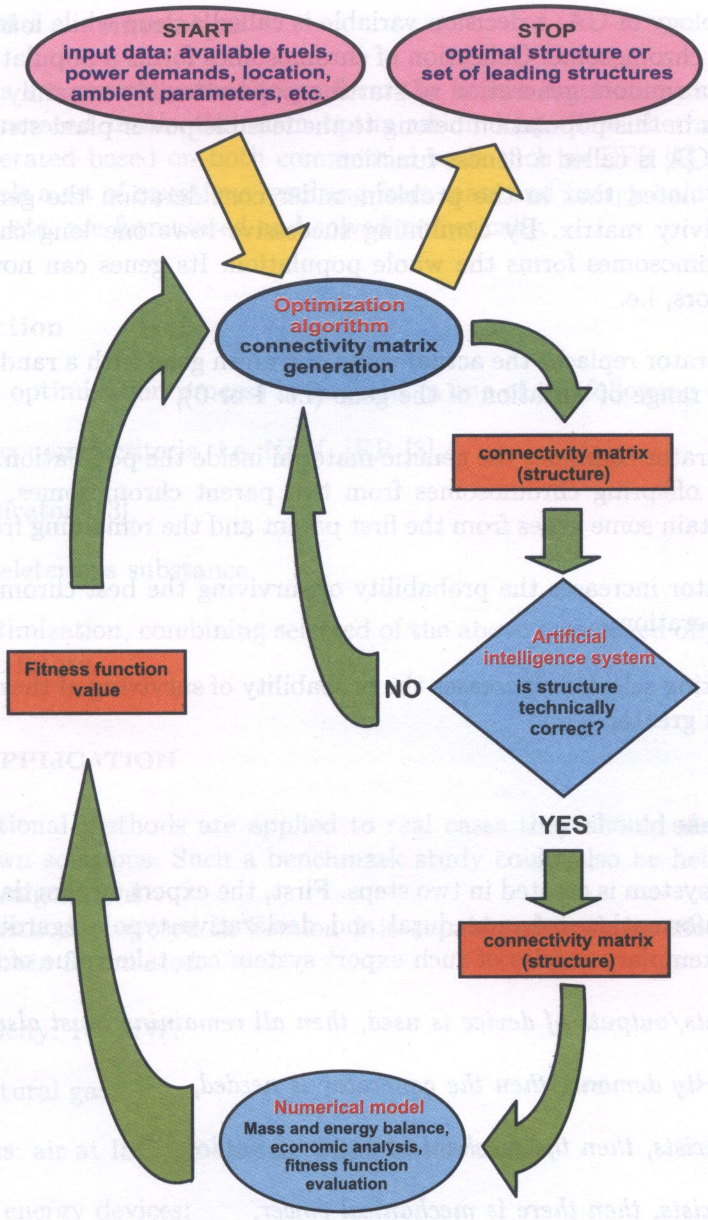

Fig. 1. The overview of proposed design process

2.1. Genetic algorithms

Genetic algorithms (GA) mimic the evolution of subsequent generations of living systems [1, 5, 10]. An important feature of this class of procedures is their randomness. This class of optimization algorithms does not suffer from the limitations of the deterministic techniques. The idea of GAs is quite straightforward so their computer implementation is fairly easy and natural. Additionally, these algorithms does not require evaluation of the sensitivity coefficients. In the presence of local minima, GAs are more reliable than their deterministic counterparts. The main and very serious drawback of these techniques is their high computational cost. This can, however, be partially mitigated by invoking parallel calculations [4].

Genetic algorithms use binary coding of the decision variables and as such are a direct analog of the evolution process of living beings. The evolutionary algorithm (EA) can be considered as a modified genetic algorithm, in which the population is coded by floating point representation [10].

Using the terminology of GA, a decision variable is called a gene while a sequence of all decision variables is termed a chromosome. Collection of chromosomes forms a population. The optimization process begins with a random generation of starting population. It certainly has to be guaranteed that all chromosomes in this population belong to the feasible power plant structures. The objective function utilized by GA is called a fitness function.

It should also be noted that in the problem under consideration the genes are identical with rows of the connectivity matrix. By combining successive rows one long chromosome is defined. Collection of all chromosomes forms the whole population. Its genes can now be modified by the set of genetic operators, i.e.

mutation – the operator replaces the actual value of a given gene with a random number belonging to the admissible range of variation of the gene (i.e. 1 or 0),

crossover – the operator combines the genetic material inside the population. The simple crossover creates a pair of offspring chromosomes from two parent chromosomes, so that the offspring chromosomes contain some genes from the first parent and the remaining from the second parent,

cloning – the operator increases the probability of surviving the best chromosome by duplicating it in the next generation,

selection – the ranking selection increases the probability of surviving of these chromosomes whose fitness function is greater.

2.2. Knowledge base

The knowledge base system is created in two steps. First, the expert system database is constructed, containing logical information (of procedural and declarative type) regarding the system under investigation. The exemplary entries of such expert system can take value of:

- *if one of the inputs/outputs of device is used, then all remaining must also be used,*
- *if there is electricity demand, then the generator is needed,*
- *if the generator exists, then the mechanical power is needed,*
- *if the expander exists, then there is mechanical power,*
- *if the steam turbine exists, then there is mechanical power,*
- *if the steam turbine exists, then the steam generator is needed,*
- *possible steam generator is waste-heat boiler,*
- *if essential part of system is missing (coefficients of the connectivity matrix are equal to 0), then the structure is infeasible,*
- *if the exhaust gases are connected to the steam turbine inlet, then the structure is infeasible,*
- *etc.*

In the second step, the data collected in the expert system database together with the generated power plant structure (e.g. gas turbine exists, waste-heat boiler exists, etc.) are processed and the conclusions are drawn. Both commercial and in-house codes are used to program logical operations in accordance with the knowledge base system.

2.3. Numerical model — simulation

The numerical models are generally used to perform the fitness function evaluation. These models are automatically generated inside the main optimization loop. The thermodynamic models of the structure are generated based on both commercial tools such as EES [7] and in-house Fortran codes. Using those tools a set of equations resulting from mass and energy balances, state equations, chemical equilibrium, etc. are formulated and solved numerically.

2.4. Objective function

It is decided that the optimization process is targeted in one of the following objective functions:

- some of UNIDO economic criteria, i.e. NPV, IRR [3],
- ecological cost indicator [13],
- unit emission of deleterious substance.

The multi-criteria optimization, combining selected of the above mentioned objective functions, will also considered in the future.

3. BENCHMARK APPLICATION

Before new computational methods are applied to real cases they should always be validated on the basis of well-known solutions. Such a benchmark study could also be helpful for tuning of all proposed models and algorithms.

To check if the method proposed in Section 2 is capable of working effectively, the following benchmark case has been formulated:

- demand for electricity: 100 MW,
- available fuels: natural gas,
- ambient conditions: air at ISO conditions; water not available,
- available singular energy devices:
  - compressors – max. 5 units,
  - expanders – max. 5 units,
  - combustors – max. 5 units,
  - heat exchangers – max. 5 units,
  - electric generator – 1 unit,
- general task: build the power plant structure which presents the highest possible energy efficiency.

All the singular energy devices are pre-defined by assumed characteristic parameters like internal efficiency, pressure ratios (for compressors, expanders), fuel conversion ratio (for combustors), heat transfer effectiveness (for heat exchangers), etc.

As water is not available, all the power plant structures, generated by the algorithm, represent some kind of gas turbine cycle and a few exemplary layouts have been presented in Fig. 2. The connectivity matrices resulting from those structures lead immediately to chromosomes representing just few individuals in a whole population.

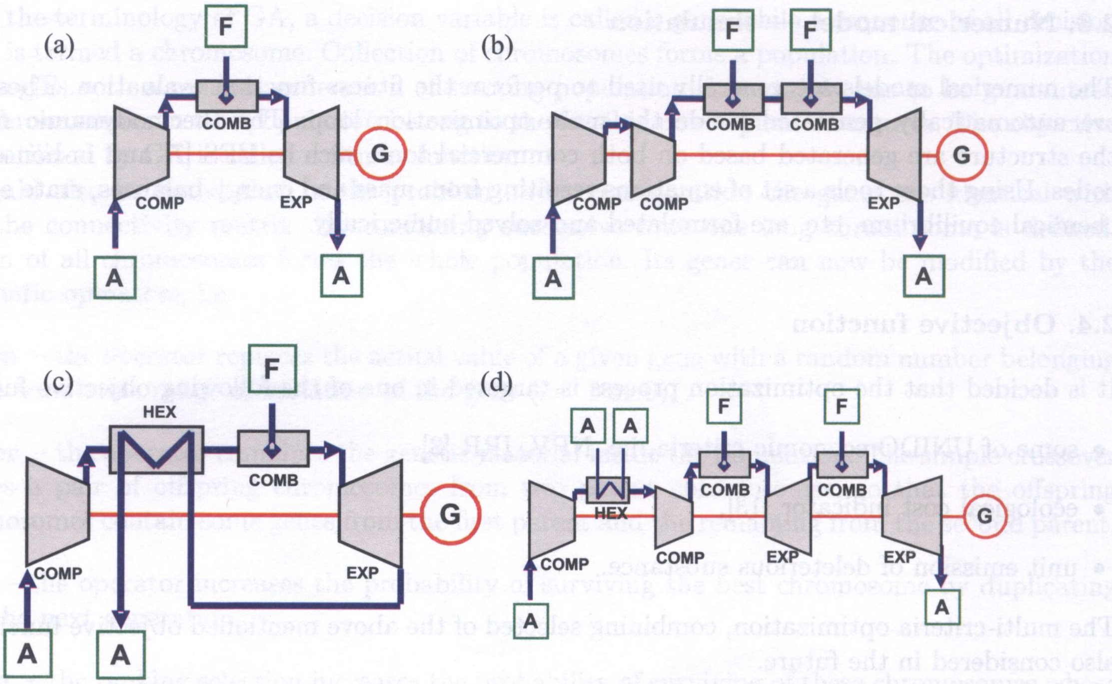

Fig. 2. Exemplary structures to be (possibly) generated by optimisation algorithm. Legend: A – ambient, F – fuel, G – electric generator, COMP – compressor, HEX – heat exchanger, COMB – combustor, EXP – expander

Table 1. Exemplary connectivity matrix (nonzero rows and columns only) for regenerative GT (cf. Fig. 2c)

			Outputs						
			A #1	F #1	COMP #1	HEX #1	HEX #2	COMB #1	EXP #1
Inputs	A	#1	0	0	0	1	0	0	0
	COMP	#1	1	0	0	0	0	0	0
	HEX	#1	0	0	1	0	0	0	0
		#2	0	0	0	0	0	0	1
	COMB	#1	0	1	0	0	0	0	0
		#2	0	0	0	0	1	0	0
	EXP	#1	0	0	0	0	0	1	0

Possibility of in-series connection of devices of the same type (Fig. 2b) lets to optimize also some operating parameters. For instance, if thermodynamic objective function is formulated and pressure ratio of single compressor is assumed to be equal to 2, the algorithm can choose two compressors with overall pressure ratio of 4 or three compressors (with overall pressure ratio of 8) and so on. Similar optimization capabilities apply to combustors, expanders and heat exchangers. However, if an economic objective function is used (e.g. NPV, IRR), then one needs to build the software for calculation of costs properly.

The exemplary connectivity matrix based on layout for regenerative gas turbine GT cycle (Fig. 2c) is presented in Table 1. The ambient and fuel supply have been considered as boundary elements of the structure.

The electric generators visible in Fig. 2 are not included in connectivity matrix as they serve as power balance equipment. The power generated or consumed by rotating devices is delivered (or extracted) to common shaft and transmitted to electric generator. Power shaft balance is a separate section of the simulation model.

The fitness function selected for the benchmark application is the energy efficiency, defined as a ratio of the overall electric power N_{el} to the rate of chemical energy of fuel $\dot{E}_{ch}$,

$$\eta_E = \frac{N_{el}}{\dot{E}_{ch}} \to \max. \tag{1}$$

Taking into account gas turbine thermodynamic theory [6] it is widely known that the energy efficiency of GT system increases when the cycle pattern approaches the Carnot one. This feature allows one to evaluate the correctness and effectiveness of proposed structure synthesis method.

The structure found by the algorithm as optimal should be close to the *ultimate cycle* characterized by:

- division of compression to many intercooled steps,
- division of expansion to many reheated steps (i.e. sequential combustion),
- heat recuperation.

4. Numerical example

Taking into account all available energy devices (i.e. 5 compressors, 5 expanders, 5 combustors, 5 heat exchangers, 10 ambient inputs, 15 ambient outputs and 15 fuel outputs) and the fact that devices can have more than one input and one output (eg. heat exchanger: 2 inputs, 2 outputs), the resulting connectivity matrix is large (55 columns $\times$ 40 rows = 2200 entries). As a result, each chromosome consisted of 2200 gens (0 or 1).

The numerical tests showed that it is impossible to generate staring population in fully random approach. After 100 000 attempts no feasible structure was obtained. The reason is that the connectivity matrix, that corresponds to feasible structure, is 'almost' not populated. Namely, maximum one '1' is allowed in each row of connectivity matrix (i.e. I/O of the device can be connected only to one I/O port of subsequent device, otherwise the structure is not feasible).

In the second step of numerical test, the fully randomized generator of starting population was exchanged with *random-expert system* generator. The required requirements and limitations were provided by incorporated expert system. The entries of such expert system were as follows:

- *at least one ambient output must be used,*
- *if one of the inputs/outputs of device is in use (connected), then all remaining ports must also be used (connected),*
- *etc.*

The classic genetic operators, like mutation and cross-over, need special attention as well. Classic mutation (gene change to opposite value) or cross-over in random X-ing point may easily lead to not feasible structures (i.e. not all I/O of the device used). This can also be avoided by incorporation of another expert system, with possible entries:

- *crossover point may be chosen only in the end or beginning of row of connectivity matrix,*
- *if mutation forces I/O to be used, then all remaining I/O of the device must be used as well,*
- *etc.*

The idea of modified genetic algorithm is presented in Fig. 3.

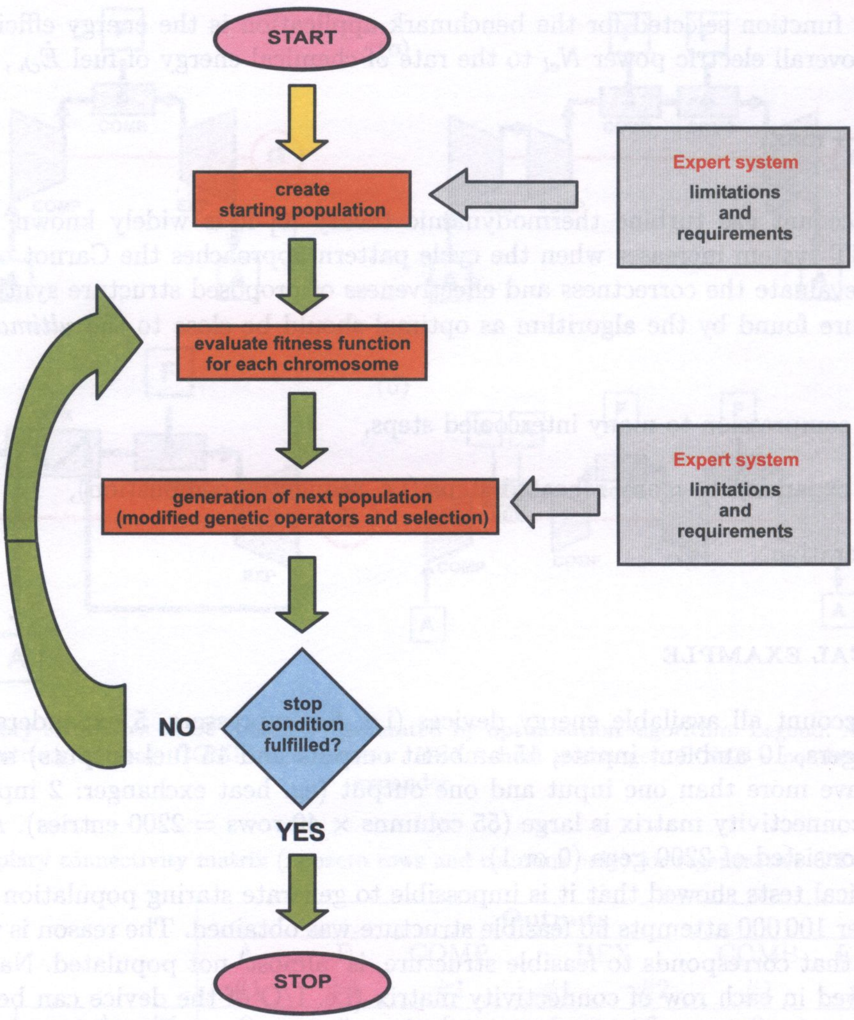

Fig. 3. Modified genetic algorithm (incorporated expert system)

5. Preliminary results

The preliminary results of automatic synthesis of CHP systems (structures) with corresponding energy efficiency are presented in the Fig. 4. Presented results are chosen as the best solutions (i.e. the highest efficiency) from among starting population generated by proposed *random-expert system*. Having in mind problems signalized in Section 4, further work is anticipated to propose modified genetic operators applicable for the problem at hand.

6. Conclusions

Since significant investments inside the European Union within the next 15 years are expected in both the electricity production as well as in energy transfers, the precise decision-making processes are already desperately needed. The major objective of this paper was to propose an application of a new methodology to design of power systems in a fully automatic way. Proposed methodology utilizes the current artificial intelligence tools like genetic algorithm and expert system to search for the best structure of the power station. This structure is composed from basic energy devices and it is reflected within the connectivity matrix. Each structure is evaluated by calculation of one of the UNIDO economic criteria.

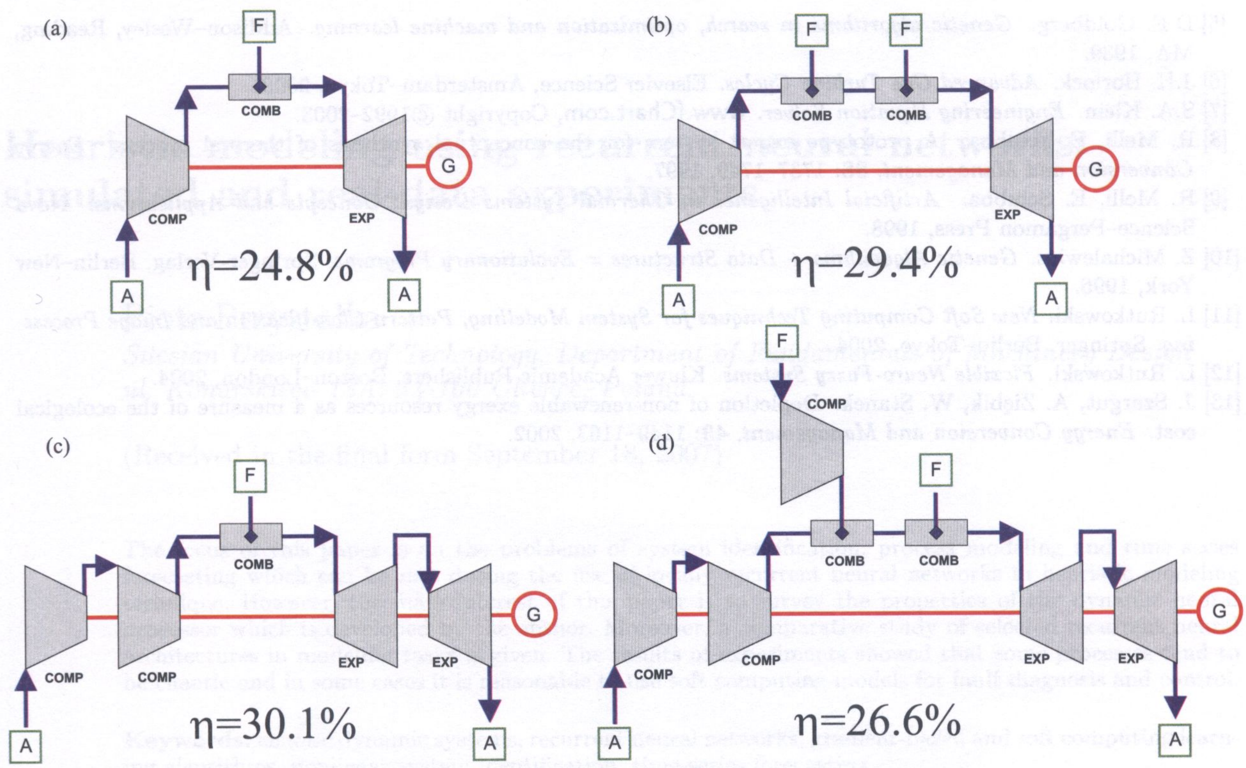

Fig. 4. Results-generated structures. Legend: A – ambient, F – fuel, G – electric generator, COMP – compressor, HEX – heat exchanger, COMB – combustor, EXP – expander

Even though the benchmark application seems to be simple, the complexity of problem at hand is high. The resulting connectivity matrix is large (55 columns $\times$ 40 rows = 2200 entries). Special attention must be focused towards building new modified genetic operators to avoid generation of structures that are not technically correct.

This paper only discusses the idea of the proposed methodology which will be eventually applied to the synthesis of combined (heat and power) CHP cycle. Nevertheless, the first step — primary benchmark studies of GT system discussed in Section 3 already produced encouraging results confirming usefulness of the method and its effectiveness. Preliminary results are presented in Section 5, and ongoing research is aimed at further tests and development of proposed method.

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References

[1] J. Arabas. *Lectures on Evolutionary Algorithms* (in Polish). Wydawnictwa Naukowo-Techniczne, Warszawa, 2001.

[2] T. Baeck, D.B. Fogel, Z. Michalewicz, eds. *Handbook of Evolutionary Computations.* Computation Intelligence Library, Institute of Physics Publishing, 1997.

[3] W. Behrens, P.M. Hawranek. *Manual for the Preparation of Industrial Feasibility Studies.* Warszawa: United Nations Industrial Development Organisation, 1993–2003.

[4] R.A. Białecki, T. Burczyński, A. Długosz, W. Kuś, Z. Ostrowski. Evolutionary shape optimization of thermoelastic bodies exchanging heat by convection and radiation. *Computer Methods in Applied Mechanics and Engineering*, **194**(17): 1839–1859, 2005.

[5] D.E. Goldberg. *Genetic algorithms in search, optimization and machine learning.* Addison–Wesley, Reading, MA, 1989.
[6] J.H. Horlock. *Advanced Gas Turbine Cycles.* Elsevier Science, Amsterdam–Tokyo, 2003.
[7] S.A. Klein. *Engineering Equation Solver.* www.fChart.com, Copyright ©1992–2003.
[8] R. Melli, E. Sciubba. A prototype expert system for the conceptual synthesis of thermal process. *Energy Conversion and Management*, **38**: 1737–1749, 1997.
[9] R. Melli, E. Sciubba. *Artificial Intelligence in Thermal Systems Design: Concepts and Applications.* Nova Science–Pergamon Press, 1998.
[10] Z. Michalewicz. *Genetic Algorithms + Data Structures = Evolutionary Programs.* Springer-Verlag, Berlin–New York, 1996.
[11] L. Rutkowski. *New Soft Computing Techniques for System Modelling, Pattern Classification and Image Processing.* Springer, Berlin–Tokyo, 2004.
[12] L. Rutkowski. *Flexible Neuro-Fuzzy Systems.* Kluwer Academic Publishers, Boston–London, 2004.
[13] J. Szargut, A. Ziębik, W. Stanek. Depletion of non-renewable exergy resources as a measure of the ecological cost. *Energy Conversion and Management*, **43**: 1149–1163, 2002.