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# Optimisation Algorithm for the Profit from Operation of a Barge Train versus Settings of the Main Engine During Inland Navigation in Varying Water Resistance Conditions (Part 2)

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**Abstract**

The test calculations were carried out according to the profit optimisation algorithm of inland waterway transport means operation considering a division of the waterway into sectors detailed described in the first part of this work. The push barge train consists of Bizon push boat and two OBP-500W barges were used to the calculations. Before a practical application for specified economical analysis it is required to collect a huge number of data to obtain an appropriate result. The main input data consists of (i) structure of the costs and their variation in relation to engine speed, and (ii) propulsion-resistance characteristics for wide spectrum of train' draughts and waterway depths. The results of optimisation calculations confirmed correctness and usefulness of the developed algorithm.

**Keywords:** inland waterway transport, barge train, optimisation, economic estimation

## List of a Symbols Specific for Optimisation Algorithm – GA

*c_strategy* – designation of the crossover strategy,
*elitism* – logic variable for inclusion or exclusion of the elitist selection strategy,

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| | | |
|---|---|---|
| $f$ | – | objective function, |
| $f_{eval}$ | – | fitness function values for particular individuals, |
| $l$ | – | length of chromosome string for individual, |
| $l_d$ | – | length of chromosome sub-string for decision variable, |
| $n\_x\_site\_min$ | – | min. number of the crossover points, |
| $n\_x\_site\_min$ | – | max. number of the crossover points, |
| $N_e$ | – | number of elitists, |
| $N_{gen}$ | – | number of generations in the simulation, |
| $N_{pop}$ | – | size of populations, number of individuals in the population, |
| $p_c$ | – | probability of a crossover, |
| $p_m$ | – | probability of mutation, |
| $p_u$ | – | probability of updating, |
| $u$ | – | preference function for the optimisation criteria, |
| $\mathbf{x}$ | – | decision variable vector, |
| $x_{dmin}$ | – | lower limit of the decision variable $x_d$, |
| $x_{dmax}$ | – | upper limit of the decision variable $x_d$, |
| $\Delta x_d$ | – | resolution of decision variable coding. |

# 7. Test Computations (Example): Optimisation of the Operating Costs of a Barge Train versus Settings of the Main Engine in Inland Navigation at Varying Water Resistance Conditions

## 7.1. The optimisation model

For the (i) verification of the optimisation algorithm described in the subsection 5 and (ii) demonstration of possibilities of a practical application of the algorithm, an optimisation analysis of a pushed barge train: Bizon III (pushboat) + 2 OBP 500 (barges), $N_t = 1$, was conducted and presented on a round-trip Wrocław–Szczecin–Wrocław, $N_j = 2$. The draught in the river water on the sectors $h$ was adopted on the assumption of the average draught of the barge $T = 1.4$ m, $N_d = 1$, confirmed by the operating experience for the Odra river. The division of the route on the resistance characteristic sectors, for average navigable water given in Table 1, $N_s = 8$.

A mathematic formulation of the cost optimisation task versus the speed of the ME may be as follows:

– the search for the minimum of the objective function: $f(\mathbf{x}) \rightarrow \min!$,
– fulfilling the constraints: $g(\mathbf{x}) \leqslant 0$,
– for the decision variables: $x_{dmin} \leqslant x_d \leqslant x_{dmax}$,

where: $f(\mathbf{x})$ – the objective function, which its minimum shall be searched for; $\mathbf{x}$ – the decision variable vector $x_d$, $g(\mathbf{x})$ – the constraints, $x_{dmin}$ and $x_{dmax}$ – the lower and upper limits of the decision variable range, respectively.

It is assumed that the objective function is the commuting costs between Wrocław and Szczecin, $f(\mathbf{x}) = C_C(\mathbf{x})$ €. None of the constraints type $g(\mathbf{x}) \leqslant 0$ are formulated. The decision variable is the speed of the ME $n(N_t, N_s, N_T, N_j) = n(1,i,1,j)$ with the borderline conditions: $n_{min} = 1150$ min$^{-1} \leqslant n(1,i,1,j) \leqslant n_{max} = 1400$ min$^{-1}$, $i = 1, 2, \ldots, N_s$, $N_s$ – number of resistance characteristic sectors, $j = 1$ for the Wrocław-Szczecin direction, $j = 2$ for the Szczecin-Wrocław direction. The formulated optimisation task is specified in Table 2. As the optimisation analysis will be carried out for a specific type or variant of the train, $N_t$, and the adopted operating draught $T$, $N_d$, the objective function may be written also in the form: $f(N_t, N_d) = C_C(N_t, N_d)$.

Table 1

**The division of the Wrocław–Szczecin–Wrocław route on the resistance characteristic sectors, for average navigable water [2]**

| Sector, $i$ | Start, km | Finish, km | Length, km | Speed of stream $v_p(i)$, km/h |
|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 |
| 1 | 255 | 283 | 28 | 3.06 |
| 2 | 283 | 378 | 95 | 4.14 |
| 3 | 378 | 469 | 91 | 4.43 |
| 4 | 469 | 516 | 47 | 4.28 |
| 5 | 516 | 542 | 26 | 4.86 |
| 6 | 452 | 618 | 166 | 4.43 |
| 7 | 618 | 666 | 48 | 4.75 |
| 8 | 666 | 735 | 69 | 3.74 |

The total cost of the round route $C_C(\mathbf{x})$ is the sum of the (i) total cost of a barge train in the time of technological operations, costs not connected directly with the ship's movement, $C_T$, and (ii) total cost of the barge train movement, $C_V(\mathbf{x})$:

$$C_C(\mathbf{x}) = C_T + C_V(\mathbf{x}) \tag{1}$$

It is assumed that the constant costs, $C_T$, are the sum of: the depreciation costs during the technological operations, $C_A$, repair costs during the technological operations, $C_R$, personal costs during the technological operations, $C_P$, consumed fuel oil costs during the technological operations, $C_O$, extra costs without any direct relationship with the movements of a barge train, $C_D$:

$$C_T = C_A + C_R + C_P + C_O + C_D \tag{2}$$

From the formal viewpoint one may assume that the constant costs will represent the optimisation parameters: their values are fixed and do not depend upon the decision variables. Values of those costs are shown in Table 3, lines 7 through 11.

Table 2

**The specifications of the formulated optimisation task: optimisation of the total voyage cost $C_C$ versus the ME speed $n(1,i,1,j)$**

| Pos. | Description | Formulation | Comments |
|---|---|---|---|
| 1 | 2 | 3 | 4 |
| 1 | Objective function | $f(\mathbf{x})$ | commuting costs between Wrocław and Szczecin, $C_C(N_t, N_d)= C_C(1,1)$, €, $N_t$ – number of the train types or variant, $N_d$ – number of operating draught $T$ values |
| 2 | Constraints | $g(\mathbf{x}) \leqslant 0$ | none[1] |
| 3 | Borderline conditions | $x_{dmin} \leqslant x_d \leqslant x_{dmax}$ | $n_{min}$ = 1150 min$^{-1}$ $\leqslant n(1,i,1,j) \leqslant n_{max}$ = 1400 min$^{-1}$, $i$ =1, 2, ...,$N_s$, $N_s$ – number of resistance characteristic sectors, $j$ =1 for the Wrocław-Szczecin direction, $j$ =2 for the Szczecin-Wrocław direction |

[1] The speed of a barge train moving upstream has to be greater than zero so that such a barge train will not move backwards. The speed of a barge train moving downstream has to be high enough to maintain manoeuvrability.

As regards the total cost of the barge train movement, $C_V(\mathbf{x})$, it is assumed that it is the sum of: amortization cost, $C_A(\mathbf{x})$, cost of repairs, $C_R(\mathbf{x})$, personnel cost, $C_p(\mathbf{x})$, total fuel cost, $C_o(\mathbf{x})$:

$$C_V(\mathbf{x}) = C_A(\mathbf{x}) + C_R(\mathbf{x}) + C_p(\mathbf{x}) + C_o(\mathbf{x}) \tag{3}$$

Finally, it is assumed that the total fuel cost, $C_o(\mathbf{x})$, is the sum of: the cost of fuel used by the main engines, $C_s(\mathbf{x})$, fuel cost used by the current generators, $C_a(\mathbf{x})$:

$$C_o(\mathbf{x}) = C_s(\mathbf{x}) + C_a(\mathbf{x}) \tag{4}$$

The algorithm applied to determine the value of the operating costs of a train, dependent on movement, that is directly the ME speed $n$, will be the subject of separate writing. The issue of predicting the operating costs of a barge train is also dealt with in detail in e.g. [1].

The presented classic formulation of the optimisation task should be extended by the optimisation model parameters. Those are factors being the elements of a mathematic model of the task and whose values are determined in the optimisation model and do not change in a single simulation. The adopted parameters of the optimisation model of the ME speed versus the total voyage costs are summarised in Table 3.

The value of the operating costs of a barge train in the individual sectors and for selected ME speeds $n$ are the input data for developing the optimisation algorithm. A proper assessment of those costs is very hard to obtain in practice and, at the same time, is of key importance for reliability of the results of the optimisation analysis. In the present paper, there were used cost data as estimated in reliance on

Table 3

**The parameters of the optimisation model of the ME speed *n* versus the total voyage costs $C_C$**

| Pos. | Description | Designation | Unit | Value |
|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 |
| 1 | Number of the classes of the operating draught $T$ | $N_d$ | – | 6 |
| 2 | Number of the water resistance specific sections | $N_s$ | – | 8 |
| 3 | Number of the classes of the water depth $h$ | $N_h$ | – | 4 |
| 4 | River water current speed in the sections | $v_p(1)$ | km·h$^{-1}$ | 3.06 |
| | | $v_p(2)$ | km·h$^{-1}$ | 4.14 |
| | | $v_p(3)$ | km·h$^{-1}$ | 4.43 |
| | | $v_p(4)$ | km·h$^{-1}$ | 4.28 |
| | | $v_p(5)$ | km·h$^{-1}$ | 4.86 |
| | | $v_p(6)$ | km·h$^{-1}$ | 4.43 |
| | | $v_p(7)$ | km·h$^{-1}$ | 4.75 |
| | | $v_p(8)$ | km·h$^{-1}$ | 3.74 |
| 5 | Fuel oil density | $\rho_f$ | kg·l$^{-1}$ | 0.845 |
| 6 | Fuel oil unit price | $P_f$ | €·l$^{-1}$ | 0.32 |
| 7 | Depreciation costs during the technological operations | $C_{AT}(1)$ | € | 92.70 |
| | | $C_{AT}(2)$ | € | 92.70 |
| 8 | Repair costs during the technological operations | $C_{RT}(1)$ | € | 179.22 |
| | | $C_{RT}(2)$ | € | 179.22 |
| 9 | Personal costs during the technological operations | $C_{PT}(1)$ | € | 217.50 |
| | | $C_{PT}(2)$ | € | 217.50 |
| 10 | Consumed fuel oil costs during the technological operations | $C_{OT}(1)$ | € | 118.64 |
| | | $C_{OT}(2)$ | € | 118.64 |
| 11 | Extra costs without any direct relationship with the movements of a barge train | $C_D(1)$ | € | 20.00 |
| | | $C_D(2)$ | € | 20.00 |

the true data from ODRATRANS S.A.[1] [2]. As an example, in the Table 4 there are quoted the operating costs of a barge train in one selected waterway sector and for the one way upstream traffic of such a barge train. For the ME speeds *n* as generated through the algorithm, other than those tabulated, the values of the individual costs were calculated by interpolation.

Because based on the developed algorithm, its computer-aided implementation is developed, the computer model of the optimisation was to be extended by some control variables to keep a grip as computer simulations proceeded. Those variables are specific for the implemented optimisation algorithm. The adopted parameters to control the course of the genetic optimisation are gathered in Table 7.

[1] Odratrans S.A. is the largest inland shipping company in Poland. Odratrans S.A. was founded in 1946 and is based in Wroclaw, Poland.

## 7.2. "Genetic" model

### 7.2.1. General

The optimisation model as defined in sub-section 6.1 may not be directly employed to optimisation making use of GA, therefore the model is re-formulated to a genetic model that fulfils particular requirements for such algorithms. The formulated genetic model comprises:
- the chromosome structure,
- the fitness function,
- the genetic operators,
- the search control parameters.

Table 4

**Cost of operation of barge train in Wrocław–Szczecin route, sector 255–283 km [2]**

| No. | Variable | Value | | | | | |
|---|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| Engine speeds | | | | | | | |
| 1 | $n$, min$^{-1}$ | 1,150 | 1,200 | 1,250 | 1,300 | 1,350 | 1,400 |
| The dependence of the hour fuel use in the function of the motor speeds and the ship's speed on the lentic water, for resistance characteristic sectors | | | | | | | |
| 2 | $V_o$, km·h$^{-1}$ | 9.50 | 9.93 | 10.34 | 10.72 | 11.08 | 11.40 |
| 3 | $B_h$, kg·h$^{-1}$ | 31.7 | 35.5 | 39.5 | 43.7 | 48.4 | 53.5 |
| Fuel cost on the sectors | | | | | | | |
| 4 | $v_b$, km·h$^{-1}$ | 12.56 | 12.99 | 13.40 | 13.78 | 14.14 | 14.46 |
| 5 | $t$, h | 2.23 | 2.16 | 2.09 | 2.03 | 1.98 | 1.94 |
| 6 | $B_s$, kg | 70.69 | 76.68 | 82.56 | 88.71 | 95.83 | 103.79 |
| 7 | $B_{sl}$, l | 84.66 | 91.83 | 98.87 | 106.24 | 114.77 | 124.30 |
| 8 | $C_s$, € | 27.15 | 29.45 | 31.70 | 34.07 | 36.80 | 39.86 |
| 9 | $C_a$, € | 6.97 | 6.75 | 6.54 | 6.35 | 6.27 | 6.06 |
| 10 | $C_o$, € | 34.12 | 36.20 | 38.24 | 40.42 | 43.07 | 45.92 |
| Total movement cost of the barge train | | | | | | | |
| 11 | $C_A$, € | 6.89 | 6.67 | 6.49 | 6.27 | 6.12 | 5.99 |
| 12 | $C_R$, € | 13.32 | 12.90 | 12.49 | 12.13 | 11.83 | 11.59 |
| 13 | $C_P$, € | 16.17 | 15.66 | 15.15 | 14.72 | 14.36 | 14.07 |
| 14 | $C_O$, € | 34.12 | 36.20 | 38.20 | 40.42 | 43.07 | 45.92 |
| 15 | $C_V$, € | 70.50 | 71.43 | 72.33 | 73.54 | 75.38 | 77.57 |

### 7.2.2. Chromosome structure

The adopted sequence of coding of variables in a chromosome is shown in Table 5. As the bit notation on a string of the finite length $l_d$ permits coding a finite number, then the relationship between the lowest $x_{dmin}$ and the highest $x_{dmax}$ values of the decision variables, the gene length $l_d$ and the resolution $\Delta x_d$, assumes the form:

$$\Delta x_d = \frac{x_{d\,\max} - x_{d\,\min}}{2^{l_d} - 1} \tag{5}$$

The lowest and the highest values of the decision variables, i.e. $x_{dmin}$ and $x_{dmax}$ are the gene lengths $l_d$ are so selected that the resolution $\Delta x_d$ will not exceed one (Table 5). In Table 5 the adopted lengths of strings selected to represent the relevant decision variables are listed. In all the chromosome string is $l$ = 128 bits long. The adopted chromosome structure allows an analysis of nearly $2.81 \cdot 10^{14}$ design variants.

Table 5

**The specifications of the bit representation of the decision variables of the genetic model of the optimisation of total operating costs $C_c$ versus the ME speed $n$**

| No. | Decision variable $n(1,i,1,j)$ | Designation, $x_d$ | Gene length, $l_d$ | Value | | |
|---|---|---|---|---|---|---|
| | | | | Lower $x_{dmin}$ | Upper $x_{dmax}$ | Resolution $\Delta x_d$ |
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 1 | $n(1,1,1,1)$ | $x_1$ | 8 | 1150 | 1400 | 0.98 |
| 2 | $n(1,2,1,1)$ | $x_2$ | 8 | 1150 | 1400 | 0.98 |
| 3 | $n(1,3,1,1)$ | $x_3$ | 8 | 1150 | 1400 | 0.98 |
| 4 | $n(1,4,1,1)$ | $x_4$ | 8 | 1150 | 1400 | 0.98 |
| 5 | $n(1,5,1,1)$ | $x_5$ | 8 | 1150 | 1400 | 0.98 |
| 6 | $n(1,6,1,1)$ | $x_6$ | 8 | 1150 | 1400 | 0.98 |
| 7 | $n(1,7,1,1)$ | $x_7$ | 8 | 1150 | 1400 | 0.98 |
| 8 | $n(1,8,1,1)$ | $x_8$ | 8 | 1150 | 1400 | 0.98 |
| 9 | $n(1,1,1,2)$ | $x_9$ | 8 | 1150 | 1400 | 0.98 |
| 10 | $n(1,2,1,2)$ | $x_{10}$ | 8 | 1150 | 1400 | 0.98 |
| 11 | $n(1,3,1,2)$ | $x_{11}$ | 8 | 1150 | 1400 | 0.98 |
| 12 | $n(1,4,1,2)$ | $x_{12}$ | 8 | 1150 | 1400 | 0.98 |
| 13 | $n(1,5,1,2)$ | $x_{13}$ | 8 | 1150 | 1400 | 0.98 |
| 14 | $n(1,6,1,2)$ | $x_{14}$ | 8 | 1150 | 1400 | 0.98 |
| 15 | $n(1,7,1,2)$ | $x_{15}$ | 8 | 1150 | 1400 | 0.98 |
| 16 | $n(1,8,1,2)$ | $x_{16}$ | 8 | 1150 | 1400 | 0.98 |
| Chromosome length $l$: | | | 128 | Number of the possible solutions: | | $\approx 2.81 \cdot 10^{14}$ |

### 7.2.3. Fitness function

The fitness function assumed in 6.1 defines the type of the formulated optimisation task, it being min! Whereas the optimisation algorithm, GA, is applicable to tasks type max! For the purpose of (i) re-formulating a task type min! into a task type max!, and (ii) achieving the desired convergence of the algorithm, the optimisation criterion is defined in the form of the preference function $u$. While defining the mathematic form of the preference function, the following requirements are attributed thereto:

– the actual values of the preference function have to rise monotonic with regard to the criterion,
– the values of the partial preference function have to be standardised to one,
– the values of the preference function have to be absolute (dimensionless).

In Table 6 the adopted form of the preference function is shown, which meets the specified criteria.

Table 6

**The form of the preference function $u$ adopted to the genetic model of the optimisation of total operating costs $C_C$ versus the ME speed $n$**

| Objective function $f(\mathbf{x})$ | | | | |
|---|---|---|---|---|
| Designation | Description | | Type | |
| 1 | 2 | | 3 | |
| $C_C$ | Total costs of a to-and-from voyage | | min! | |
| Preference function $u(\mathbf{x})$ | | | | |
| Designation | Form | $C_{Cmax}$ | $r$ | Type |
| 4 | 5 | 6 | 7 | 8 |
| $u$ | $\left(\frac{C_{C\max} - C_C}{C_{C\max}}\right)$ | 15,000 | 5.0 | max! |

The highest value $C_{Cmax}$ of the criterion achievable in computations is established based on results of test computations. The proper assumption of the highest value ensured that the value of the preference function for the criterion type min! did not reach a negative value in the course of serial computations. The value of the power factor $r$ for the required convergence of the algorithm was adopted after test computations.

In Figures 5 and 6 the influence of the parameters $C_{Cmax}$ and $r$ of the preference function $u$ upon the variableness of the function for the criterion type min! is illustrated. With a fixed value of the power factor $r$ the rising parameter $C_{Cmax}$ results in the decreasing sensitivity of the preference function $u$ to varying values of the criterion $C_C$ with some greater values of the preference function. With the fixed greatest value of the criterion $C_{Cmax}$ the decreasing value of the power factor $r$ results in the reduced sensitivity of the preference function to changes in the values of the criterion, also with some greater values of the preference function.

Assuming the form of the preference function $u(\mathbf{x})$ from Table 6 for the optimisation criterion $C_C$ the formulated optimisation task consists in looking for the greatest value of the task-related optimisation criterion $f$:

$$f(\mathbf{x}) = u(\mathbf{x}) \tag{6}$$

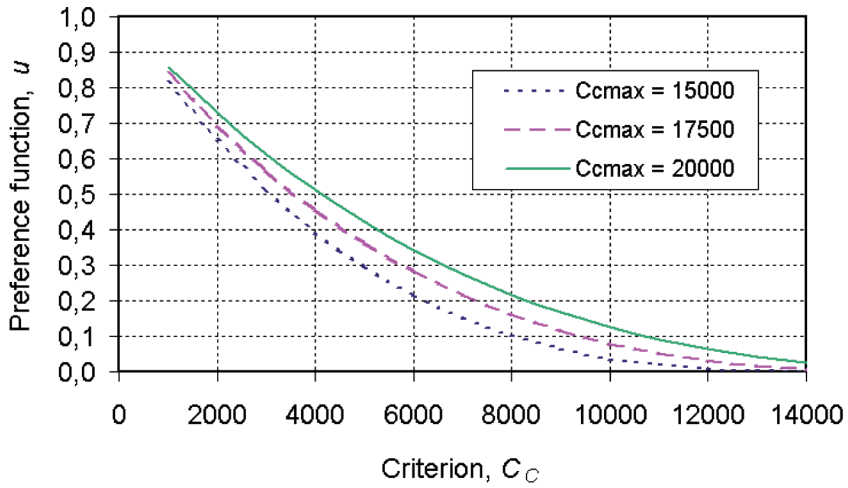


Fig. 5. The impact of the greatest value of the assessment criterion $C_{Cmax}$ upon the value of the preference function for the criterion type min!; the value of the power factor $r = 3$ adapted after test computations

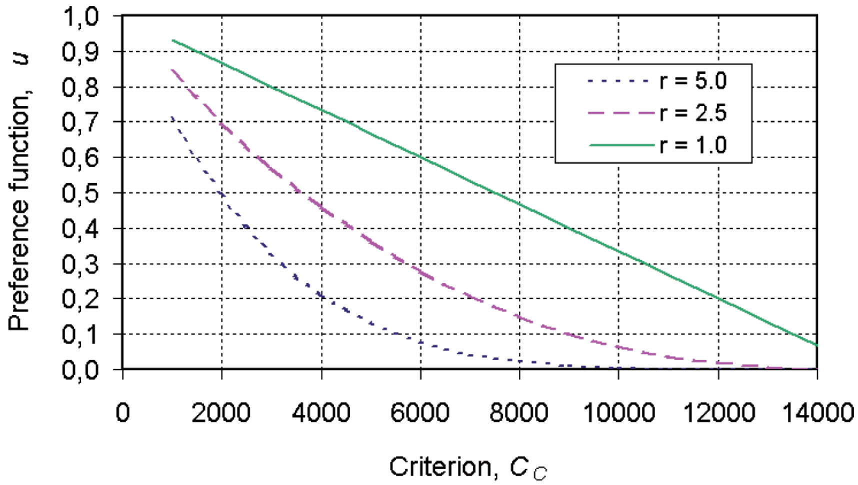


Fig. 6. The impact of the power factor $r$ upon the value of the preference function for the criterion type min!; the greatest value of the assessment criterion $C_{Cmax}$ = 15,000 adapted after test computations

Because the objective function $f(\mathbf{x})$ as determined by the relationship (6) is defined, single-valued, rising, assumes real values and positive within the space being searched, then it is directly assumed as the fitness function.

### 7.2.4. Genetic operators

The developed GA creates variants of a new generation, through the implementation of the basic operators of selection, mutation and crossover, and in addition, the updating operator and elitist strategy.

In the work, the proportional selection operator is implemented that relies on the roulette wheel concept. A simple gene mutation is adopted. An *n*-site random crossing operator is developed. An increased effectiveness of the algorithm is attained by applying the additional updating operator and, through implementing the elitist strategy, off-springs are replaced by selected parental individuals. The adopted values of the parameters of the genetic operators are summarised in Table 7.

### 7.2.5. Control parameters

With a defined genetic model, one course of the optimisation is characterized by values of ten control parameters (Table 7). The number of generations is fixed at the highest practically permissible level, because of the duration of computations. The population magnitude was found out after a detailed analysis.

With the fixed number of generations and size of population, the values of the other control parameters were determined based on test computations, considering the required divergence of the algorithm. The adopted control parameters and their values are gathered in Table 7.

Table 7

**The parameters to control the conduct of the computer aided genetic implementation of the optimisation of the total voyage cost $C_c$ versus the ME speed $n$**

| Pos. | Designation | Description | Value |
|---|---|---|---|
| 1 | 2 | 3 | 4 |
| 1 | $N_g$ | number of generations | 5,000 |
| 2 | $N_i$ | population size | 2,000 |
| 3 | $N_p$ | number of elitists | 3 |
| 4 | $p_m$ | probability of a mutation | 0.1 |
| 5 | $p_c$ | probability of a crossover | 0.6 |
| 6 | *c_strategy* | designation of the crossover strategy (0 for the fixed number of the crossover points; 1 for a random number of the crossover points) | 1 |
| 7 | *n_x_site_min* | min. number of the crossover points | 1 |
| 8 | *n_x_site_max* | max. number of the crossover points | 5 |
| 9 | $p_u$ | probability of updating | 0.1 |
| 10 | elitism | logic variable for inclusion (*elitism* = *yes*) or exclusion (*elitism* = *no*) of the elitist selection strategy | yes |

### 7.2.6. Results of the optimisation computations

In Figures 7, 8 and 9 the results of the genetic optimisation from the point of view of the minimisation of the total costs $C_C$ of a round route are presented.

In Figure 7 the evolutions of the greatest $f_{max}$, lowest $f_{min}$ and mean $f_{aver}$ values of fitness function $f$ as well as of the total costs $C_C$ of a round route are shown as a simulation proceeds. Amid the mentioned factors, variability of the maximum value of the fitness function $f_{max}$ is the most significant. It informs on the actual speed of the convergence of the algorithm and of the number of generations as indispensable to reach a 'saturation' of the fitness function. Because the number of variants is fixed per generation, knowing the number of the generations as necessary to 'saturate' the fitness function also denotes the awareness of the necessary number of computations of criteria and constraints. The number has a direct impact upon the duration of the computations.

The algorithm reveals a strong convergence and one may assume that the fitness function achieved its 'saturation' prior to completion of the simulation, Fig. 8. The most significant rise of maximum of the fitness function occurred during the first 1,579 generations, from $f_{max}$ = 5,132/110,000 = 0.0467 in the first generation, to $f_{max}$ = 5,746/110,000 = 0.0522 in the 1,579$^{th}$ generation. At the end of the simulation the maximum of the fitness function reached $f_{max}$ = 5,771/110,000 = 0.0525. For duration of the entire simulation the maximum of the fitness function $f_{max}$ rose from $f_{max}$ = 0,0467 in the first generation to $f_{max}$ = 0.0525 in the 5,000$^{th}$ generation. Through 5,000 generations the maximum of the fitness function rose by $\Delta f_{max}$ = 0.0058, including $\Delta f_{max}$ = 0.0055 during the first 1,579 generations, and $\Delta f_{max}$ = 0.0003 during the subsequent 3,421 generations. This denotes that 32% of the computation effort permitted reaching 94.8% of the change in the maximum of the fitness function $f_{max}$. The other 78% of the computation effort permitted reaching 5.2% of the change in the maximum of the fitness function $f_{max}$.

In Figure 9 the evolutions of the (i) maximum of the fitness function $f_{max}$, (ii) values of the criterion, (iii) total costs $C_C$ of a round route for the subsequently found best variants are shown. One may notice the expected general tendency towards reaching more favourable values of the criterion, falling the total costs $C_C$ of around route, with the rising maximum of the fitness function $f_{max}$. It is also noticeable that during the last 3,421 generations, i.e. 78% of the computation time, the global properties of the population of variants improved, those properties being described by the maximum value of the fitness function $f_{max}$; however that did not lead to any significant improvement in the value of the criterion.

In Figure 10 the evolutions of the objective function, the total costs $C_C$, of a round route for the subsequently found best variants are shown. During a simulation falling values of the total costs $C_C$ of a round route can be seen.

The decision variable vector **x** that represents the best variant found in the 3,434$^{th}$ generation, Fig. 11, assumes the form:

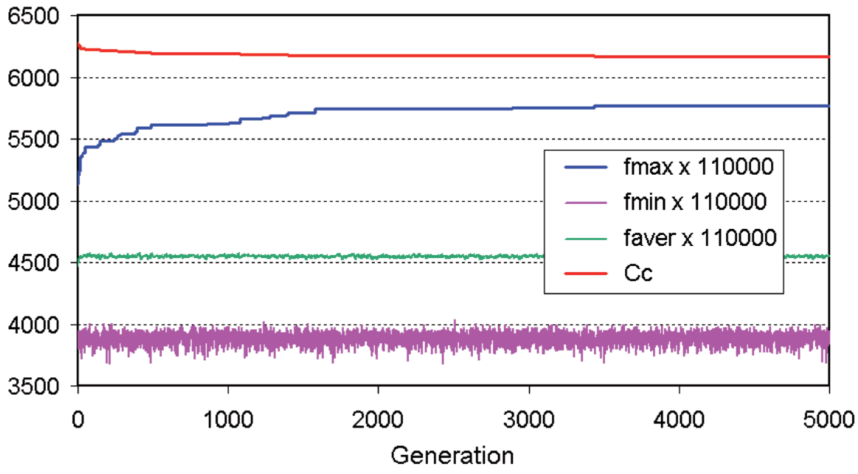


Fig. 7. The result of the genetic optimisation of the total costs $C_C$ of a round route; the evolutions of the greatest $f_{max}$, lowest $f_{min}$ and mean $f_{aver}$ values of the fitness function and of the total costs $C_C$ of a round route during a simulation; the values of the fitness function is multiplied by 110,000 to adjust the suitable scale

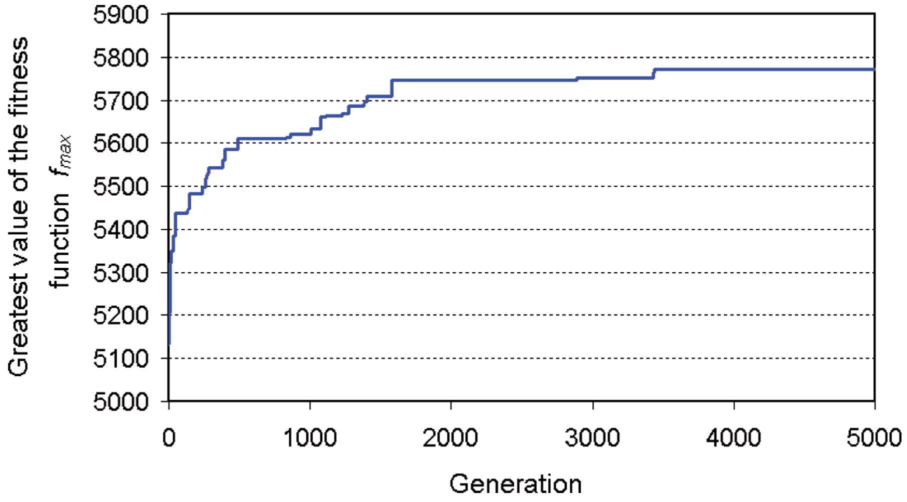


Fig. 8. The result of the genetic optimisation of the total costs $C_C$ of a round route; the evolutions of the greatest $f_{max}$ value of the fitness function during a simulation; the values of the fitness function is multiplied by 110,000 to adjust the suitable scale

$$\mathbf{x}^* = [1172.64, 1155.91, 1155.91, 1157.87, 1268.11, 1158.86, 1158.86, 1151.97,$$

$$1235.63, 1400.00, 1398.03, 1398.03, 1397.05, 1391.14, 1392.13, 1399.02]^T.$$

The appropriate optimal value of the criterion of the total costs of a round route $C_C(1,1)$, is:

$$C_C(1,1)^* = 6167.73 \text{ €}.$$

The decision variable vector $\mathbf{x}$ that represents the variant adopted to manual test calculations in Section 3. [3] is expressed as:

$$\mathbf{x}_M = [1293,\ 1293,\ 1293,\ 1293,\ 1293,\ 1293,\ 1293,\ 1293,$$
$$1383,\ 1383,\ 1383,\ 1383,\ 1383,\ 1383,\ 1383,\ 1383]^T.$$

The appropriate optimal value of the total costs of a round route $C_{C,M}(1,1)$ is:

$$C_{C,M}(1,1)^* = 6279.77 \text{ €}.$$

The decision variable vector $\mathbf{x}$ that represents the best variant proposed in the report of ODRATRANS S.A. [2] has the form:

$$\mathbf{x}_{OT} = [1150,\ 1150,\ 1150,\ 1150,\ 1150,\ 1150,\ 1150,\ 1150,$$
$$1350,\ 1350,\ 1350,\ 1350,\ 1350,\ 1350,\ 1350,\ 1350]^T.$$

The appropriate optimal value of the total costs of a round route $C_{C,OT}(1,1)$ is:

$$C_{C,OT}(1,1)^* = 7516.56 \text{ €}.$$

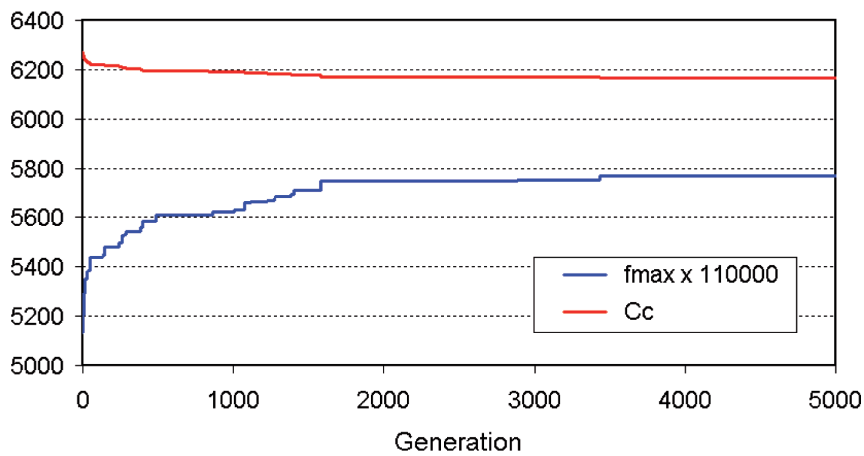


Fig. 9. The result of the genetic optimisation of the total costs $C_C$ of a round route; the evolutions of the greatest value $f_{max}$ of the fitness function and of the total costs $C_C$ of a round route during a simulation; the values of the fitness function is multiplied by 110,000 to adjust the suitable scale

### 7.2.7. Conclusions

The achieved results show that the optimisation analysis as completed with the use of the developed algorithm permits achieving, under the assumed sailing conditions, more favourable values of the operating costs of a barge train adopted under the research:

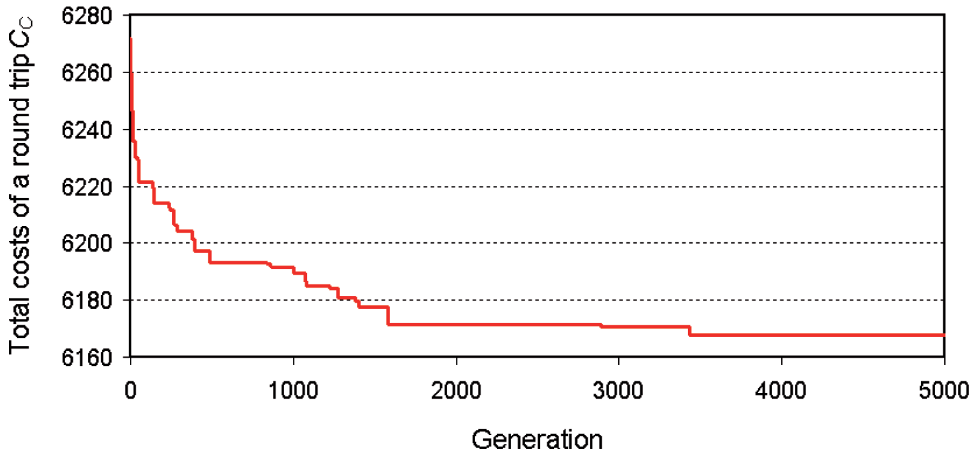


Fig. 10. The result of the genetic optimisation of the total costs $C_C$ of a round route; the evolution of the total costs $C_C$ of a round route during a simulation

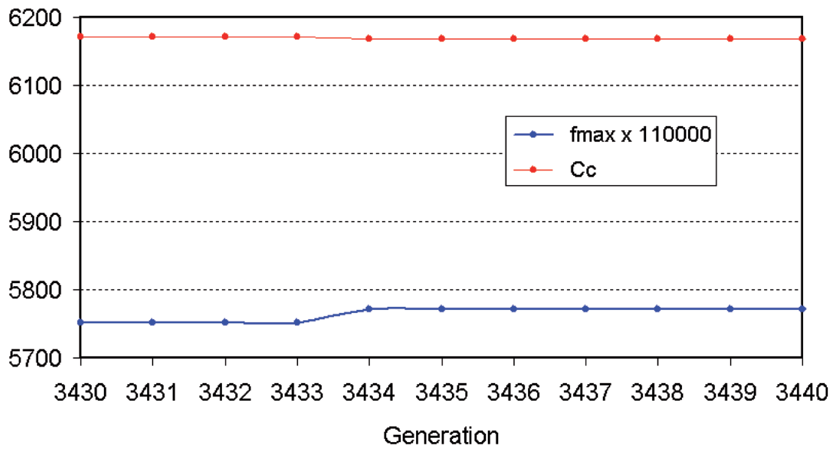


Fig. 11. The result of the genetic optimisation of the total costs $C_C$ of a round route; the changes to the greatest value $f_{max}$ of the fitness function and of the total costs $C_C$ of a round route in the 3,434$^{th}$ generation, in which the algorithm found the best variant; the values of the fitness function is multiplied by 110,000 to adjust the suitable scale

$C_C(1,1)^* = 6167.73$ € $< C_{C,M}(1,1)^* = 6279.77$ € $< C_{C,OT}(1,1)^* = 7516.56$ €.

Based on the presented results of the optimisation computations of the operating costs of a BIZON barge train in varying resistance conditions on the Odra River and data given by barge train operator prove the correctness of the developed algorithm and computational tool.

# 8. Test Computations (Example): Optimisation of the Profit from Operation of a Barge Train versus Settings of the Main Engine in Inland Navigation at Varying Water Resistance

## 8.1. Optimisation Model

The optimisation model to optimise the profit on the operation of a BIZON barge train with respect to the settings of the main engine in inland navigation in varying water resistance conditions on the Odra River was developed based on the data applied to the example of computation included in Sections 3 and 5 [2] that contained data derived from operation, with true values of the income $I_a$ and operating costs $C_C$ to the ME speed of a barge train comprised of a push-boat Bizon III and two barges OBP-500 operated by ODRATRANS SA on the round route Wrocław-Szczecin-Wrocław.

More detailed information are specified in the sub-section 6.1.

A mathematic formulation of the profit optimisation task versus the speed of the ME may be as follows:

– the search for the maximum of the objective function: $F(\mathbf{x}) \rightarrow \max!$,
– fulfilling the constraints: $g(\mathbf{x}) \leqslant 0$,
– for the decision variables: $x_{dmin} \leqslant x_d \leqslant x_{dmax}$,

where: $F(\mathbf{x})$ – the objective function, which its maximum shall be searched for; $\mathbf{x}$ – the decision variable vector $x_d$, $g(\mathbf{x})$ – the constraints, $x_{dmin}$ and $x_{dmax}$ – the lower and upper limits of the decision variable range, respectively.

It is assumed that the objective function is a profit earned in a single voyage of a barge train on the round route between Wrocław and Szczecin, $F(\mathbf{x}) = Z_a(\mathbf{x}) = I_a(\mathbf{x}) - C_C(\mathbf{x})$, €. None of the constraints type $g(\mathbf{x}) \leqslant 0$ are formulated. The decision variable is the speed of the ME $n(N_t, N_s, N_d, N_j) = n(1,i,1,j)$ with the borderline conditions: $n_{min} = 1150\ \text{min}^{-1} \leqslant n(1,i,1,j) \leqslant n_{max} = 1400\ \text{min}^{-1}$, $i = 1, 2, \ldots, N_s$, $N_s$ – number of resistance characteristic sectors, $j = 1$ for the Wrocław-Szczecin direction, $j = 2$ for the Szczecin-Wrocław direction. The formulated optimisation task is specified in Table 8. As the optimisation analysis will be carried out for (i) a specific type or variant of the barge train, and (ii) adopted operating draught $T$ the objective function may be written also in the form: $F(N_t, N_d) = C_C(N_t, N_d)$.

The parameters adopted to the model the optimisation of the profit from the operation of the barge train $Z_a$ versus the ME speed $n$ are contained in Table 3. The adopted parameters to control the course of the genetic optimisation are gathered in Table 7.

Table 8

**The specifications of the formulated task of the optimisation of the profit from the operation of the barge train $Z_a$ versus the ME speed $n$**

| Pos. | Description | Formulation | Comments |
|---|---|---|---|
| 1 | 2 | 3 | 4 |
| 1 | Objective function | $F(\mathbf{x})$ | profit from the operation of the barge train in a single voyage $Z_a(N_t, N_d) = I_a(N_t, N_d) - C_C (N_t, N_d) = I_a(1, 1) - C_C(1, 1)$, €, $N_t$ – number of the train types or variant, $N_d$ – number of operating draught $T$ values |
| 2 | Constraints | $g(\mathbf{x}) \leqslant 0$ | none[1] |
| 3 | Borderline conditions | $x_{dmin} \leqslant x_d \leqslant x_{dmax}$ | $n_{min}$ = 1150 min$^{-1}$ $\leqslant n(1,i,1,j) \leqslant n_{max}$ = 1400 min$^{-1}$ $i$ =1, 2, ..., $N_s$, $N_s$ – number of resistance characteristic sectors, $j$ = 1 for the Wrocław-Szczecin direction, $j$ =2 for the Szczecin-Wrocław direction |

[1] The speed of the barge train moving upstream has to be greater than zero so that such a barge train will not move backwards. The speed of the barge train moving downstream has to be high enough to maintain manoeuvrability.

## 8.2. "Genetic" model

### 8.2.1. General

The optimisation model as defined in sub-section 7.1 is re-formulated to a genetic model that fulfils particular requirements for such an algorithm. The formulated genetic model comprises:
– the chromosome structure,
– the fitness function,
– the genetic operators,
– the search control parameters.

### 8.2.2. Chromosome structure

The adopted sequence of coding of variables in a chromosome is shown in Table 5. In Table 5 the adopted lengths of strings selected to represent the relevant variables are listed as well. In all the chromosome string is $l$ = 128 bits long. The adopted chromosome structure allows an analysis of nearly $2.81 \cdot 10^{14}$ design variants.

### 8.2.3. Fitness function

The objective function assumed in sub-section 7.1 defines the type of the formulated optimisation task, it being max!. For the purpose of achieving the desired convergence of the algorithm, the optimisation function is substituted by the appropriate form of the preference function $u$. In Table 9 the adopted form of the preference function is shown.

Table 9

**The form of the preference function $u$ adopted to the model the genetic optimisation of the profit $Z_a$ from the operation of the barge train versus the ME speed $n$**

| Objective function $F(\mathbf{x})$ | | | | |
|---|---|---|---|---|
| Designation | Description | | Type | |
| 1 | 2 | | 3 | |
| $Z_a$ | Annual profit | | max! | |
| Preference function $u(\mathbf{x})$ | | | | |
| Designation | Form | $Z_{amaxx}$ | $r$ | Type |
| 4 | 5 | 6 | 7 | 8 |
| $u$ | $\left(\frac{Z_a}{Z_{a\max}}\right)^r$ | 8,000 | 10.0 | max! |

The highest value $Z_{amax}$ of the criterion achievable in computations is established based on results of test computations. The value of the power factor $r$ for the required convergence of the algorithm was adopted after test computations.

In Figures 12 and 13 the influence of the parameters $Z_{amax}$ i $r$ of the preference function $u$ upon the variableness of the function for the criterion type max! is illustrated. With a fixed value of the power factor $r$ the rising parameter $Z_{amax}$ results in the decreasing sensitivity of the preference function $u$ to varying values of the criterion $Z_a$ with some greater values of the preference function. With the fixed greatest value of the criterion $Z_{amax}$ the decreasing value of the power factor $r$ results in the reduced sensitivity of the preference function to changes in the values of the criterion, also with some greater values of the preference function.

Assuming the form of the preference function $u$ from Table 9 for the optimisation criterion $Z_a$ the formulated optimisation task consists in looking for the greatest value of the task-related optimisation criterion $F$:

$$F(\mathbf{x}) = u(\mathbf{x}) \tag{7}$$

Because the objective function $F(\mathbf{x})$ as determined by the relationship (7) is defined, single-valued, rising, assumes real values and positive within the space being searched, then it is assumed as the fitness function directly.

### 8.2.4. Genetic operators

To optimisation analyses, the proportional selection operator is implemented that relies on the roulette wheel concept. A simple gene mutation and $n$-site random crossover operator are adopted. An increased effectiveness of the algorithm is attained by applying the additional updating operator and the elitist strategy. The adopted values of the parameters of the genetic operators are summarised in Table 7.

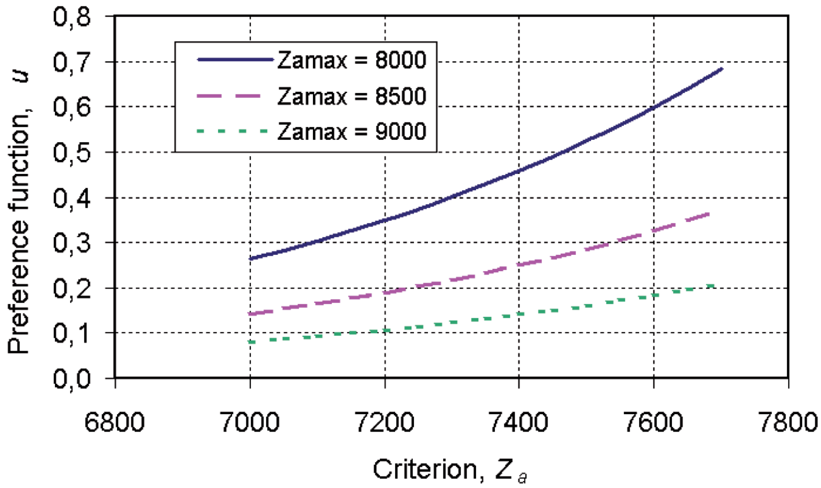


Fig. 12. The impact of the greatest value of the assessment criterion $Z_{amax}$ upon the value of the preference function; the value of the power factor $r$ = 10 adapted after test computations

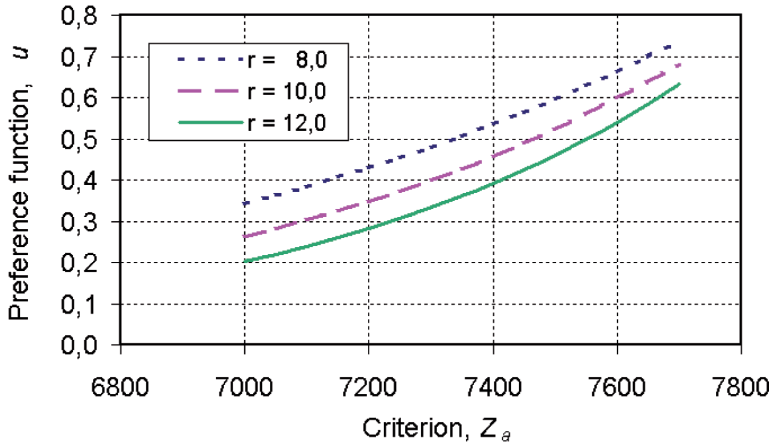


Fig. 13. The impact of the power factor $r$ upon the value of the preference function; the greatest value of the assessment criterion $Z_{amax}$ = 8,000 adapted after test computations

### 8.2.5. Control parameters

With a defined genetic model, one course of the optimisation is characterized by values of ten control parameters (Table 7). The number and magnitude of generations are fixed at the highest practically permissible level, because of the duration of computations.

With the fixed number of generations and size of population, the values of the other control parameters were determined based on test computations, considering the required divergence of the algorithm. The adopted control parameters and their values are gathered in Table 7.

### 8.2.6. Results of the optimisation computations

In Figure 14, 15, 16 and 17 the results of the genetic optimisation of the profit $Z_a$ from the operation of a barge train versus the ME speed $n$ are represented.

In Fig. 14 and 15 the evolutions of the greatest $f_{max}$, lowest $f_{min}$ and mean $f_{aver}$ values of fitness function $f$ as well as of the operating profit $Z_a$ are shown, as a simulation proceeds.

The algorithm reveals a strong convergence and one may assume that the fitness function achieved its 'saturation' prior to completion of the simulation, Fig. 16. The most significant rise of maximum of the fitness function occurred during the first 1,579 generations, from $f_{max}$ = 5,132/110,000 = 0.0467 in the first generation, to $f_{max}$ = 5,746/110,000 = 0.0522 in the 1,579$^{th}$ generation. At the end of the simulation the maximum of the fitness function reached $f_{max}$ = 5,771/110,000 = 0.0525. For duration of the entire simulation the maximum of the fitness function $f_{max}$ rose from $f_{max}$ = 0.0467 in the first generation to $f_{max}$ = 0.0525 in the 5,000$^{th}$ generation. Through 5,000 generations the maximum of the fitness function rose by $\Delta f_{max}$ = 0.0058, including $\Delta f_{max}$ = 0.0055 during the first 1,579 generations, and $\Delta f_{max}$ = 0.0003 during the subsequent 3,421 generations. This denotes that 32% of the computation effort permitted reaching 94.8% of the change in the maximum of the fitness function $f_{max}$. The other 78% of the computation effort permitted reaching 5.2% of the change in the maximum of the fitness function.

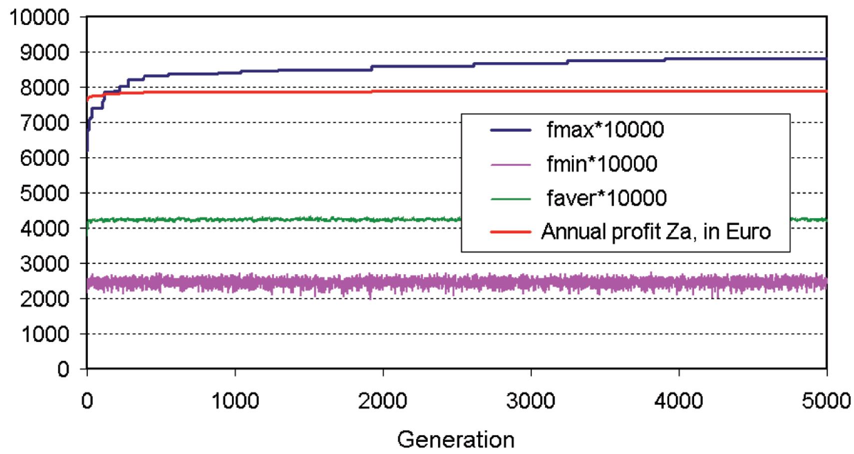


Fig. 14. The result of the genetic optimisation of the profit $Z_a$ on the operation of a barge train versus the ME speed $n$; the evolutions of the greatest $f_{max}$, lowest $f_{min}$ and $f_{aver}$ values of the fitness functions and of the profit $Z_a$ from the operation of a barge train as a simulation proceeded; the value of the fitness function is multiplied by 10,000

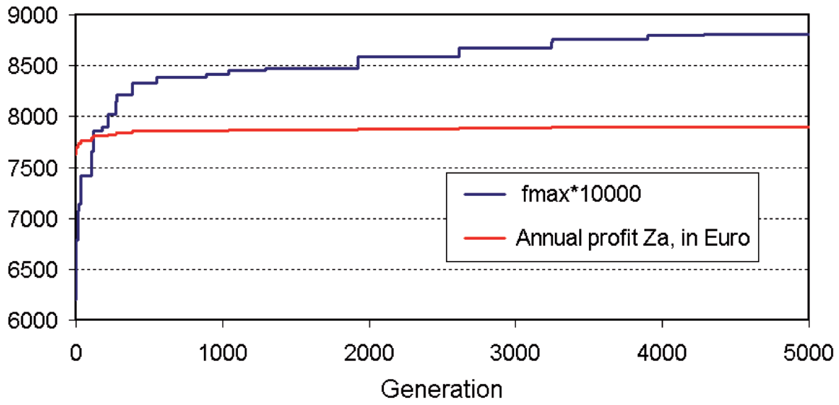


Fig. 15. The result of the genetic optimisation of the profit $Z_a$ on the operation of a barge train; the evolutions of the greatest values $f_{max}$ of the fitness function and of the profit $Z_a$ from the operation of a barge train as a simulation proceeded; the value of the fitness function is multiplied by 10,000

In Figure 15 the evolutions of the (i) maximum of the fitness function $f_{max}$, (ii) values of the criterion, profit $Z_a$ on the operation of a barge train for the subsequently found best variants are shown at the same time. One may notice the expected general tendency towards reaching more favourable values of the criterion, rising profit $Z_a$ on the operation of a barge train, with the rising maximum of the fitness function $f_{max}$. It is also noticeable that during the last 3,421 generations, i.e. 78% of the computation time, the global properties of the population of variants improved, those properties being described by the maximum value of the fitness function $f_{max}$; however that did not lead to any significant improvement in the value of the criterion.

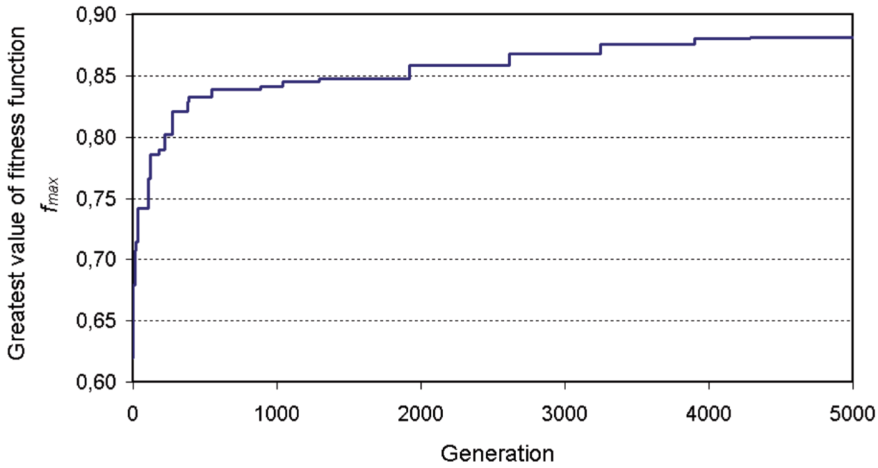


Fig. 16. The result of the genetic optimisation of the profit $Z_a$ on the operation of a barge train; the evolution of the greatest value $f_{max}$ of the fitness function during a simulation

In Figure 17 the evolutions of the (i) criterion, profit $Z_a$ on the operation of a barge train for the subsequently found best variants are shown. During a simulation the rising profit $Z_a$ on the operation of a barge train can be seen.

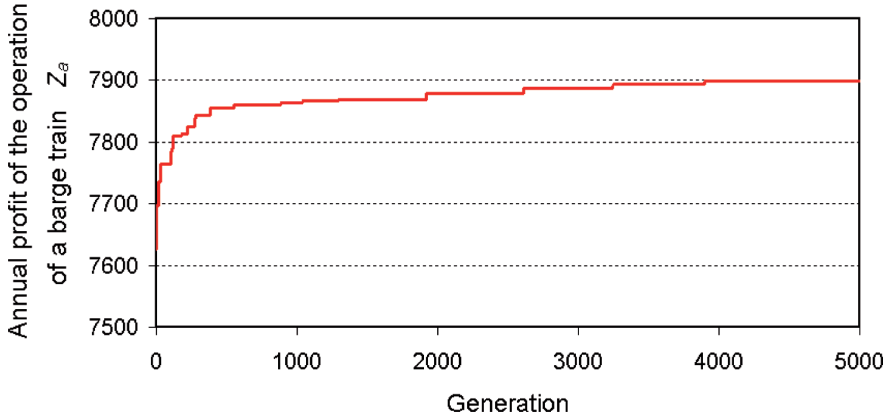


Fig. 17. The result of the genetic optimisation of the profit $Z_a$ on the operation of a barge train; the evolution of the profit $Z_a$ on the operation of a barge train during a simulation

The decision variable vector **x** that represents the best variant found in the 4,463$^{rd}$ generation, has the form:

$$\mathbf{x}^* = [1301.57, 1150.00, 1160.83, 1150.98, 1173.62, 1152.95, 1160.83, 1151.97, 1170.67, 1395.08, 1396.06, 1394.09, 1382.28, 1400.98, 1400.00, 1391.14]^T.$$

The relevant value of the criterion – the annual profit $Z_a$ on the operation of a barge train – is:

$$Z_a(1,1)^* = 7899.45 \text{ €}.$$

### 8.2.7. Conclusions

There are not any results of optimisations of the profits from operations of a BIZON barge train in varying water resistance conditions in the Odra River, published by other authors. Based on a critical assessment and an analysis of the results of the operating profits of a BIZON barge train in varying resistance conditions on the Odra River, it is considered that the developed algorithm and created computation tool – the computer aided implementation of the developed algorithm – are correct and may be employed to carry out some field computations.

## 9. Conclusions

An optimisation algorithm for a barge train that enables an optimisation of profits from the operation of a barge train versus settings of the main engine in inland navigation at varying water resistance conditions is developed. Optimisation of engine speed gave a ground here to find a maximum of profit. A computer aided computation toll, i.e. a computer implementation of the developed optimisation algorithm, is developed. The test computations are carried out: optimisation of the profits from the operation of a BIZON barge train versus settings of the main engine in inland navigation at varying water resistance in the conditions of the Odra River. The correctness of the developed optimisation algorithm and of the created computation tool is confirmed.

The developed algorithm may be (i) an effective tool in increasing the economic operating efficiency of existing inland water navigation vessels and (ii) some support while designing new inland transport means.

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