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EVOLUTIONARY OPTIMISATION OF COAL PRODUCTION IN UNDERGROUND MINES

Abstract. In the paper optimisation of coal production in multi-plant company is described. Optimisation problem and proposal of optimisation criterion were formulated. As modern solution in this area the developed evolutionary algorithm is presented. An example of calculation results is presented.

Keywords: coal production, optimisation, evolutionary algorithms, OPTiCoalMine

OPTYMALIZACJA PRODUKCJI W KOPALNIACH WĘGLA KAMIENNEGO Z WYKORZYSTANIEM ALGORYTMÓW EWOLUCYJNYCH

Streszczenie. W artykule przedstawiono zagadnienie optymalizacji produkcji w wielozakładowym przedsiębiorstwie górniczym. Zaprezentowano problem badawczy oraz kryterium optymalizacji. Jako nowe rozwiązanie w tym zakresie przedstawiono opracowany algorytm ewolucyjny. Zamieszczono również wyniki jego działania dla przykładowych danych.

Słowa kluczowe: produkcja węgla kamiennego, optymalizacja, algorytmy ewolucyjne, OPTiCoalMine

1. Introduction

There are two main directions of the mining process optimisation realised in underground coal mines: optimisation of mine elements and optimisation of production volume. In these fields various optimisation methods have been developed:

- in the area of modelling and optimisation of mine elements [i.e. 23, 26, 27],
- for optimisation of mining production [i.e. 2, 3, 8, 9, 14, 16, 20, 21, 22, 29, 32, 34, 35, 36, 38, 40, 41],
- and methods concerning mining process uncertainty [i.e. 18, 19, 25, 28, 37, 39].

In the mentioned methods mainly classical approach and analytical techniques were used (i.e. gradient methods, linear and nonlinear programming, mixed integer programming, simulation approach) for the defined particular problems.

Mining process has specific conditions of its realisation (especially underground). Designers involved in mine planning have to use in computations various data collections about geological, technical and organizational conditions of the excavations. Very often the dimension of the design problem causes difficulties in the use of the wide known analytic methods.

One of the examples is the case of mining process realised in multi-plant mining company, which includes scheduling of tens or even hundreds of excavations with different possibilities of time and equipment arrangements. The number of variants in this case equals to millions. Such problem dimension without suitable tool cannot be solved with analytic methods and, even if so, in no acceptable time.

In such case heuristic methods could be used, which are base of modern optimisation. They allow finding quite satisfactory solutions in relatively short time. Nowadays great interest is observed in natural computing methods such for example: evolutionary algorithms, swarm algorithms, artificial immune systems and artificial neural networks.

In our work we used an evolutionary algorithm which enables effective searching of the optimal solution according to the formulated objective function.

2. Evolutionary algorithms

Evolutionary algorithms could be described as computer systems for problem solving, which operation imitates the evolutionary behaviour of organisms. This imitation concerns the structure of the population as well as its functioning.

Characteristic feature of these algorithms is to create the population of individuals. In nature, individuals are living organisms, in EA individuals are usually strings (called chromosomes) or other structures (matrixes, schedules) coding solution of analysed problem. Each individual has a certain adaptation to the population environment (expressed by a value of the objective function – so called fitness function). In evolutionary algorithms higher adaptation have those individuals which more closely meet the criterion of evaluation. Creating process of offspring individuals usually takes place by recombination (crossover) of chromosomes, in which information about parental individuals are stored. Evolution of the population also includes random changes in the structure of chromosomes i.e. mutations and inversions.

The algorithm usually starts by creating a random population of individuals. Subsequently, the adaptation of each individual is estimated. The next step is selection of the parental individuals and creation of the offspring by recombination and mutation. Then adaptation of all individuals is evaluated (parents and offspring) and next population is created. The biggest chance of selection to new population have best adopted individuals. Various selection mechanism were developed (i.e. roulette selection, rank selection, elite selection etc.). The algorithm works until the stop condition is not achieved. Such condition could be expressed as defined number of generations or lack of improvement in individuals' adaptation.

There are four main groups of evolutionary algorithms:

1. genetic algorithms,
2. evolutionary programming,
3. evolutionary strategies,
4. genetic programming.

The mentioned groups differ in representation and use of genetic operators (Table 1).

Table 1

General characteristics of evolutionary algorithms

item	genetic algorithms	evolutionary programming	evolutionary strategies	genetic programming
individual	single chromosome	single chromosome	single or double chromosome*	single chromosome
coding	binary	real number (acc. to specificity of the problem)	real number (acc. to specificity of the problem)	trees
crossover	yes	no	yes*	yes
mutation	yes	yes (dominant operator)	yes	yes

* depends on a strategy type

Source: Based on: Brzychczy E.: A method for modelling and optimisation of exploitation works in a multi-plant mining enterprise. Rozprawy i Monografie, nr 245. AGH, Kraków 2012.

Like any technique evolutionary algorithms have advantages and disadvantages, but because of easy development and implementation, the possibility of multi-criteria optimisation and easy collaboration with other techniques (heuristics) their popularity nowadays has grown. Evolutionary algorithms have been already used in the mine planning issues [1, 12, 13, 15, 17, 24, 31, 33, 42, 43], more often for open-pits. Use of evolutionary algorithms in mine planning allows to take into account most of the problem constraints and specific conditions. Nowadays, in mine planning, usage of such algorithms could be a good alternative to solve problems for which traditional methods fail.

3. Optimisation proposal

Optimisation of the coal production in the multi-plant company comprises the following issues:

- choice of coal seam parts to be excavated and their order,
- selection of the equipment and its allocation to planned excavations,
- assumption of duration time of mining operations with respect to risk and uncertainty of the process.

In the case of the longwall exploitation system – number and dimensions of longwalls as well as their order should be defined. Selection of the equipment should take into account previous experiences in various possibilities of equipping longwalls in different conditions of the mining process (geological, technical or organizational).

The use of knowledge about mining process is especially important to assumption of duration time of mining operations and estimation of production volume. In this area risk and uncertainty aspects should be taken into consideration with statistical analysis of historical data and models of the mining operation characteristics (i.e. rates of the operations' advance).

None of the methods mentioned earlier are dedicated for coal production optimisation in multi-plant company with equipment allocation and uncertainty aspect. For such needs, the CPRG method was developed[1].

The optimisation problem in this method was formulated as follows: what equipment should be used under conditions of the designed longwall excavations in a mining company and what should be the rate of advance – from the point of view of the assumed criterion?

As one of the optimisation criteria, the minimisation of the coal production deviation from planned values in analysed period was proposed:

$$f = \sqrt{\sum_{i=1}^{m} (NPAv_i - NPPl_i)^2} \rightarrow min \tag{1}$$

where:

$NPAv_i$ – the estimated average value of the net production in mine (or group of mines) in *i*-th month [Mg/month],

$NPPl_i$ – the planned volume of the net production in i-th month [Mg/month],

m – the number of months in analysed period.

For finding optimal solution evolutionary algorithm was developed. Its general scheme is presented in Fig. 1.

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[1] Brzychczy E.: The planning optimisation system for underground hard coal mines. "Archives of Mining Sciences", No. 56(2), 2011, p. 161-178.

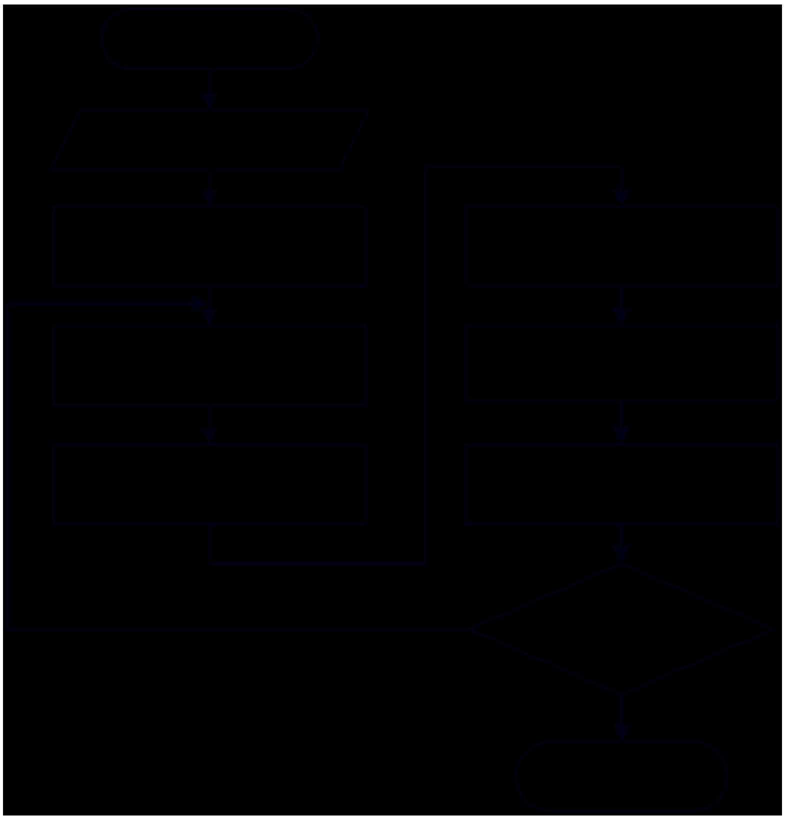

Fig. 1. General scheme of developed evolutionary algorithm
Source: Based on: Brzychczy E.: A new solution supporting the designing process of mining operations in underground coal mines. Mine Planning and Equipment Selection: proceedings of the 22nd MPES conference. Vol. 1. Drebenstedt C., Singhal R. (eds.). Dresden, Germany 14-19th October 2013, Springer 2014.

The initial data to algorithm include:

- characteristics of planned longwalls (dimensions, quality parameters of coal),
- definition of longwalls order (concerning the time dependencies),
- allocation matrix comprising longwall sets of machinery with possibility of their use in conditions of planned longwalls (possibility could be estimated with use of the historical data analysis or given by the designer),
- rates of mining operation advance (for longwall sets in planned longwalls), expressed as a random variable with normal distribution (distribution could be modelled during statistical analysis of historical data or assumed by the designer),
- planned production per month [Mg/month],
- start and end dates of optimisation (default 24 months).

Above all, settings of the algorithm should be defined including:

- individuals quantity in a base population (P),
- parental individuals quantity (λ),
- elite quantity (η),
- the number of longwall advance simulations in the planned excavations (N).

After data entry random initialization of the base population (with P individuals) is done. Individual's chromosome is represented by matrix in which each planned longwall has assigned one longwall set (according to allocation matrix).

Evaluation of population requires calculations of the operation duration time and volume of production in each longwall. In algorithm three types of the mining operations are taken into account: reinforcement, exploitation and liquidation operations. Duration time of reinforcement and liquidation operations is deterministic value expressed in months. Duration time of longwall exploitation depends on length of the longwall panel and the rate of advance (m/d), which is simulated according to assumed distribution (N times). Volume of the daily net production in the longwall is calculated as follows:

$$np = h \cdot ls \cdot \gamma \cdot r \cdot \beta \tag{2}$$

where:
h – the height of the longwall [m],
ls – the length of the longwall [m],
γ – the volume weight of coal [Mg/m3],
r – the rate of the longwall advance [m/d],
β – the losses coefficient.

After summing daily net production of longwalls working in each month, the average value of the net production in mine (or group of mine) is calculated. After N simulation, the average monthly values are estimated (*NPAvi*) and value of the fitness function is found.

After evaluation of individuals, population P is sorted and the best ηindividuals are copied to population $P^t\eta$ (as so called elite). Then creation of offspring individuals begins.

Parental individuals (the best λ individuals in population) are copied to O^t population and mutate. Because of the problem specific, in developed algorithm mutation is the only genetic operator. Mutation is done by random changes of the longwall sets in the planned longwalls according to possibilities from allocation matrix. Two types of mutation are implemented: micromutation – change is done in one longwall and macromutation – changes are done in all planned longwalls at once. The maximum number of the macromutations (ν) and threshold enabling macromutation (ε) are also the algorithm settings. After achieving the threshold enabling macromutation (lack of best solution improvement trough subsequent ε generations) in algorithm macromutation is executed.

After mutation stage evaluation of population O^t is carried out and creation of next population is done.

The stopping condition of the algorithm is lack of solutions' improvement in subsequent ε generations after execution of maximum number of the macromutations.

The presented algorithm was introduced to OPTiCoalMine calculation service[2], which is implemented in a Virtual Laboratory GridSpace2 and shared on the server ACK Cyfronet[3]. In the next section case study and results of calculations are described.

4. Case study

The case study includes five coal mines of selected coal company. The optimisation problem concerns allocation of 10 longwall sets (Table 2) in 61 planned longwalls (Table 3). Analysis includes period from 1 January 2017 to 31 December 2018 with planned monthly production at 300,000 [Mg/month].

Table 1

List of machines included in the algorithm

Set	Type of shearer	Conveyor
z1	JOY 4L	RYBNIK 850
z2	KSW 880EU	RYBNIK 850
z3	KGE 750	JOY AFC
z4	KSW 460	RYBNIK 850
z5	Strug GH 1600	4HB
z6	KGS 600	RYBNIK 850
z7	KGE 710FM	RYBNIK 850
z8	KGS 345N	HB 3E74
z9	KSW 475	RYBNIK 850
z10	KSW 1140E	RYBNIK 1100

Source: Own study.

[2] Pędziwiatr T.: OPTiCoalMine calculation service: Source code, ACC Cyfronet, Cracow 2014; Brzychczy E.: A modern tool for modelling and optimisation of production in underground coal mine, [in:] Bubak M., Kitowski J., Wiatr K. (eds.): eScience on distributed computing infrastructure: achievements of PLGrid Plus domain-specific services and tools. Springer International Publishing, 2014.

[3] Ciepiela E., Zaraska L., Sulka G.D.: GridSpace2 Virtual Laboratory Case Study: Implementation of Algorithms for Quantitative Analysis of Grain Morphology in Self-assembled Hexagonal Lattices According to the Hillebrand Method, [in:] Bubak M., Szepieniec T., Wiatr K. (eds.): Building a National Distributed e-Infrastructure – PL-Grid – Scientific and Technical Achievements. “Lecture Notes in Computer Science”, Vol. 7136, 2012, p. 240-251; Ciepiela E., Nowakowski P., Kocot J., Harężlak D., Gubała T., Mainzer J., Kasztelnik M., Bartyński T., Malawski M., Bubak M.: Managing Entire Lifecycles of e-Science Applications in GridSpace2 Virtual Laboratory – From Motivation through Idea to Operable Web-Accessible Environment Built on Top of PL-Grid e-Infrastructure, [in:] Bubak M., Szepieniec T., Wiatr K. (eds.): Building a National Distributed e-Infrastructure – PL-Grid – Scientific and Technical Achievements, “Lecture Notes in Computer Science”, Vol. 7136, 2012, p. 228-239.

Table 3

List of longwalls parameters used in the algorithm

long-wall	length	height	length of the longwall panel	volume	calorific value	sul-phur	ash	long-wall	length	height	length of the longwall panel	volume	calorific value	sul-phur	ash
	[m]	[m]	[m]	weight	[KJ /kg]	[%]	[%]		[m]	[m]	[m]	weight	[KJ /kg]	[%]	[%]
				[Mg/m^3]								[Mg/m^3]			
401	184.5	1.95	674	1.41	33815	0.58	13.13	514	111.04	2.08	444.8	1.33	33890	0.51	3.14
402	184.5	1.95	674	1.41	33815	0.58	13.13	515	249.89	2.07	911.5	1.3	32932	0.46	7.07
403	184.5	1.95	674	1.41	33815	0.58	13.13	516	252.53	2.49	446.25	1.31	33460	0.5	6.16
404	161.5	2.45	808.3	1.3	32695	0.65	10.82	414	248.5	3.9	1010	1.34	26991	0.7	12
405	161.5	2.45	808.3	1.3	32695	0.65	10.82	415	247.5	3.4	950	1.4	31407	0.8	6
406	161.5	2.45	808.3	1.3	32695	0.65	10.82	416	247.5	2.5	1200	1.41	32230	0.8	7
407	111	2.85	726	1.32	32650	0.32	5.47	417	297.5	2.35	330	1.41	30398	0.8	7
408	111	2.85	726	1.32	32650	0.32	5.47	418	244.5	1.75	970	1.38	30086	0.6	9
409	204.5	1.85	823	1.33	33046	0.84	11.35	419	200	1.85	660	1.42	26786	1.1	15
410	204.5	1.85	823	1.33	33046	0.84	11.35	310	236	2.7	1409	1.32	27500	0.5	13
411	204.5	1.85	823	1.33	33046	0.84	11.35	311	232	2.24	1771	1.33	26000	0.7	20
412	215.5	2.85	708	1.33	32813	0.63	7.84	320	249	1.98	810	1.29	31000	0.47	8.38
413	215.5	2.85	708	1.33	32813	0.63	7.84	321	238	1.92	630	1.28	31800	0.64	4.6
501	173.5	3.7	1021.9	1.38	33353	0.42	6.62	322	213	2	600	1.28	31800	0.52	5.4
502	173.5	3.7	1021.9	1.38	33353	0.42	6.62	323	241	2.44	1420	1.28	31800	0.51	4.66
503	173.5	3.7	1021.9	1.38	33353	0.42	6.62	324	154	2.39	760	1.3	31000	0.65	6.46
301	247	2.66	980	1.38	29708	0.85	11.65	325	152	2.11	760	1.3	31700	0.87	6.18
302	205	2.66	426.1	1.27	29708	0.85	11.65	420	208	1.98	1030	1.3	31700	0.66	7.3
303	245	2.53	1097	1.32	29708	0.85	11.65	421	240	2.86	940	1.32	31100	0.74	9
304	250	1.78	987	1.33	29646	0.76	11.61	422	161	1.96	960	1.3	31400	0.59	9
305	250	1.77	1180	1.28	29646	0.76	11.61	430	226	3.2	1677.4	1.36	33358	0.27	5.01
504	158.62	2.34	730.5	1.3	33748	0.43	5	431	242	3.7	1200.8	1.36	31809	0.54	6.52
505	148.89	3.42	546	1.3	33470	0.34	4.02	432	237	2.6	843	1.41	31038	0.81	15.4
506	299.82	2.92	1518.96	1.3	32701	0.3	5.36	433	246	1.7	716.3	1.39	29642	1.25	9.6
507	120.74	3.12	314.75	1.35	33921	0.68	5.61	434	240	2.5	564	1.41	30183	0.84	11
508	226.36	1.95	420	1.3	34035	0.41	2.85	435	242	2.7	1100	1.41	30320	1	7.5
509	176.38	2.97	585.5	1.27	33801	0.45	3.16	440	203	2.4	630	1.32	32542	0.72	7.8
510	166.39	2.4	520	1.31	33538	0.55	4.7	441	208	2.4	646	1.34	32991	0.66	5.77
511	104.69	3.32	568	1.31	33031	0.49	6.3	442	238	3.31	275	1.32	33266	0.46	3.77
512	121.05	2.68	828.9	1.33	33374	0.42	4.93	443	219	3.5	385	1.36	33675	0.37	4.1
513	139.98	2.32	533	1.32	33139	0.54	6.7								

Source: Own study.

Taking into account the current state and the history of used sets, machines were assigned to the longwalls with the probability of their use in given conditions. Allocation matrix of machines in the planned longwalls is shown in Table 4.

Table 4

Allocation matrix of machines in the planned longwalls

	z1	z2	z3	z4	z5	z6	z7	z8	z9	z10
401	0,9	0,1	0	0	0	0	0	0	0	0
402	0,9	0,1	0	0	0	0	0	0	0	0
403	0,9	0,1	0	0	0	0	0	0	0	0
404	0,9	0,1	0	0	0	0	0	0	0	0
405	0,9	0,1	0	0	0	0	0	0	0	0
406	0,9	0,1	0	0	0	0	0	0	0	0
407	0,9	0,1	0	0	0	0	0	0	0	0
408	0,9	0,1	0	0	0	0	0	0	0	0
409	0,9	0,1	0	0	0	0	0	0	0	0
410	0,9	0,1	0	0	0	0	0	0	0	0
411	0,9	0,1	0	0	0	0	0	0	0	0
412	0,9	0,1	0	0	0	0	0	0	0	0
413	0,9	0,1	0	0	0	0	0	0	0	0
501	0,9	0,1	0	0	0	0	0	0	0	0
502	0,9	0,1	0	0	0	0	0	0	0	0
503	0,9	0,1	0	0	0	0	0	0	0	0
301	0	0,5	0,2	0,3	0	0	0	0	0	0
302	0	0,5	0,2	0,3	0	0	0	0	0	0
303	0	0,5	0,2	0,3	0	0	0	0	0	0
304	0	0,5	0,2	0,3	0	0	0	0	0	0

cont. table 4

305	0	0,5	0,2	0,3	0	0	0	0	0	0
504	0,4	0	0,2	0,1	0,2	0,1	0	0	0	0
505	0,4	0	0,2	0,1	0,2	0,1	0	0	0	0
506	0,4	0	0,2	0,1	0,2	0,1	0	0	0	0
507	0,4	0	0,2	0,1	0,2	0,1	0	0	0	0
508	0,4	0	0,2	0,1	0,2	0,1	0	0	0	0
509	0,4	0	0,2	0,1	0,2	0,1	0	0	0	0
510	0,4	0	0,2	0,1	0,2	0,1	0	0	0	0
511	0,4	0	0,2	0,1	0,2	0,1	0	0	0	0
512	0,4	0	0,2	0,1	0,2	0,1	0	0	0	0
513	0,4	0	0,2	0,1	0,2	0,1	0	0	0	0
514	0,4	0	0,2	0,1	0,2	0,1	0	0	0	0
515	0,4	0	0,2	0,1	0,2	0,1	0	0	0	0
516	0,4	0	0,2	0,1	0,2	0,1	0	0	0	0
414	0,1	0,5	0,3	0,1	0	0	0	0	0	0
415	0,1	0,5	0,3	0,1	0	0	0	0	0	0
416	0,1	0,5	0,3	0,1	0	0	0	0	0	0
417	0,1	0,5	0,3	0,1	0	0	0	0	0	0
418	0,1	0,5	0,3	0,1	0	0	0	0	0	0
419	0,1	0,5	0,3	0,1	0	0	0	0	0	0
310	0	0	0	0	0	0	1	0	0	0
311	0	0	0	0	0	0	1	0	0	0
320	0,4	0	0	0,4	0	0	0,1	0,1	0	0
321	0,4	0	0	0,4	0	0	0,1	0,1	0	0
322	0,4	0	0	0,4	0	0	0,1	0,1	0	0
323	0,4	0	0	0,4	0	0	0,1	0,1	0	0
324	0,4	0	0	0,4	0	0	0,1	0,1	0	0
325	0,4	0	0	0,4	0	0	0,1	0,1	0	0
420	0,4	0	0	0,4	0	0	0,1	0,1	0	0
421	0,4	0	0	0,4	0	0	0,1	0,1	0	0
422	0,4	0	0	0,4	0	0	0,1	0,1	0	0
430	0	0	0	0	0	0,5	0,3	0	0,1	0,1
431	0	0	0	0	0	0,5	0,3	0	0,1	0,1
432	0	0	0	0	0	0,5	0,3	0	0,1	0,1
433	0	0	0	0	0	0,5	0,3	0	0,1	0,1
434	0	0	0	0	0	0,5	0,3	0	0,1	0,1
435	0	0	0	0	0	0,5	0,3	0	0,1	0,1
440	0,2	0,7	0	0	0,1	0	0	0	0	0
441	0,2	0,7	0	0	0,1	0	0	0	0	0
442	0,2	0,7	0	0	0,1	0	0	0	0	0
443	0,2	0,7	0	0	0,1	0	0	0	0	0

Source: Own study.

The longwall advance, which is required for duration time and production calculations, is a random variable with normal distribution and it was assigned on the basis of historical data of each combination: longwall excavation-longwall set. Selected average values of longwall advance and standard deviations are presented in Fig. 2. Furthermore, duration time of the reinforcement and liquidation works was estimated for 3 [months].

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Fig. 2. Selected average values of longwall advance and standard deviations in the planned excavations with assigned equipment
Source: Own study.

Based on the survey[4], the evolutionary algorithm settings were defined such as the number of base population P = 200, the number of parental population $\lambda = 7$ and the number of elite $\eta = 2$. The number of simulations N = 100 was assumed.

Because of heuristic nature of the evolutionary algorithm, the calculations were performed in the course of multiple, independent starts of the algorithm (n = 35 repetitions). Among the obtained values of the fitness function, the best solution was selected (shown in the Fig. 3 in red).

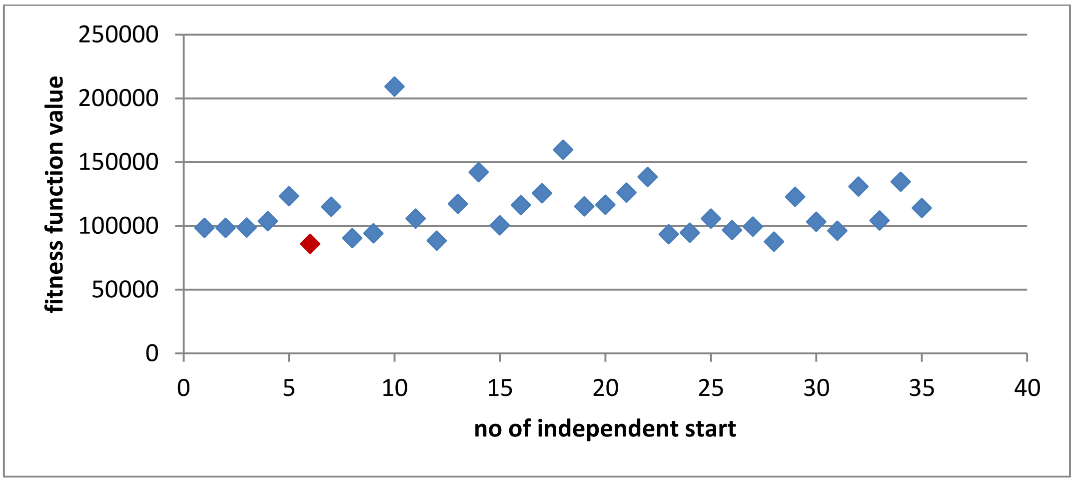

Fig. 3. Fitness function values for the best solutions in independent starts of the algorithm
Source: Own study.

[4] Brzychczy E.: A method…

The optimal solution is characterised by value of the fitness function equals to 85 667 Mg, which means a very good fit to the level of planned production (average mean error approx. 3500 Mg/month).

Table 5 shows assigned equipment in the planned longwalls and average value of the longwall advance in the best solution.

Table 5

Assigned equipment and average value of the longwall advance in the planned longwalls in the best solution

walls	machines	progress	walls	machines	progress	walls	machines	progress	walls	machines	progress
401	Z1	3,14	301	Z2	5,84	514	Z3	4,74	324	Z8	4,47
402	Z1	5,38	302	Z2	7,40	515	Z3	5,79	325	Z7	4,74
403	Z1	4,06	303	Z4	7,22	516	Z1	4,54	420	Z1	7,26
404	Z1	6,62	304	Z3	7,13	414	Z3	5,29	421	Z8	6,54
405	Z1	3,89	305	Z3	7,74	415	Z3	5,20	422	Z4	5,77
406	Z1	5,73	504	Z5	3,41	416	Z2	7,08	430	Z9	3,64
407	Z1	5,31	505	Z4	6,23	417	Z2	3,74	431	Z7	6,72
408	Z2	3,62	506	Z1	5,50	418	Z2	5,44	432	Z6	4,08
409	Z1	4,55	507	Z1	4,08	419	Z2	4,59	433	Z10	3,14
410	Z1	3,89	508	Z4	4,32	310	Z7	4,10	434	Z10	2,76
411	Z1	5,32	509	Z1	5,28	311	Z7	6,16	435	Z7	4,34
412	Z1	4,48	510	Z6	8,59	320	Z7	4,42	440	Z2	5,38
413	Z2	4,73	511	Z1	4,00	321	Z4	5,43	441	Z5	5,43
501	Z1	3,16	512	Z5	5,93	322	Z1	4,26	442	Z1	4,40
502	Z2	4,44	513	Z1	4,00	323	Z1	6,23	443	Z5	6,07
503	Z2	4,27									

Source: Own study.

In Fig. 4, the estimated values of coal production with a planned values and standard deviation for the optimal solution are shown.

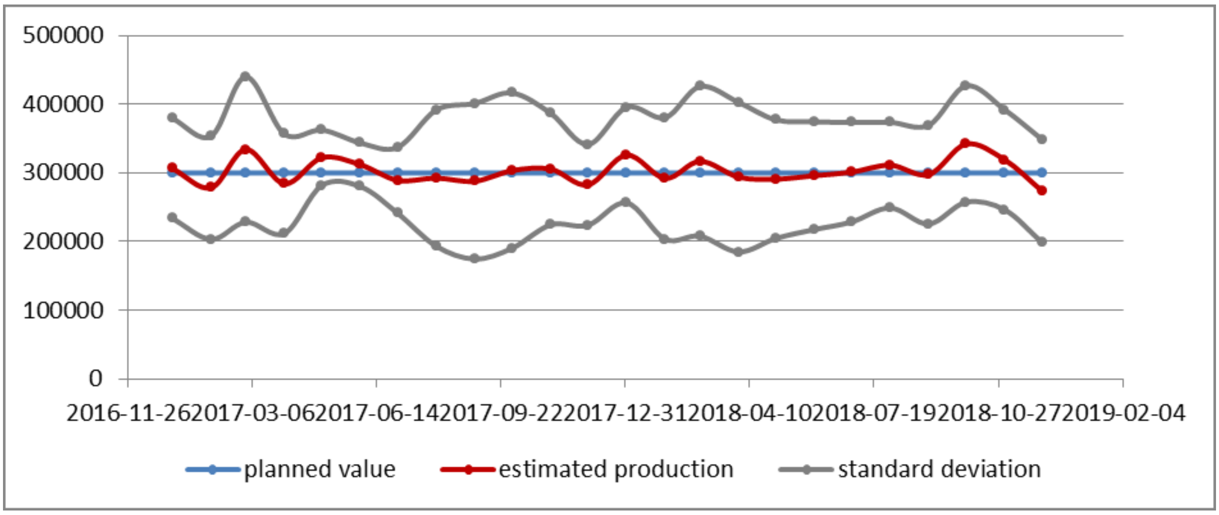

Fig. 4. Planned and estimated coal production (Mg/month) with a standard deviation in the optimal solution

Source: Own study.

On the chart satisfactory fitting of the estimated values to the planned level of production in analysed period can be seen. It should be also emphasized that additional information about uncertainty (production deviation) related to chosen solution could be very useful in decision making, especially considering the production risk management.

The fragment of schedule for the optimal solution for the period from 31 December 2015 to 31 December 2018 is shown in Fig. 5.

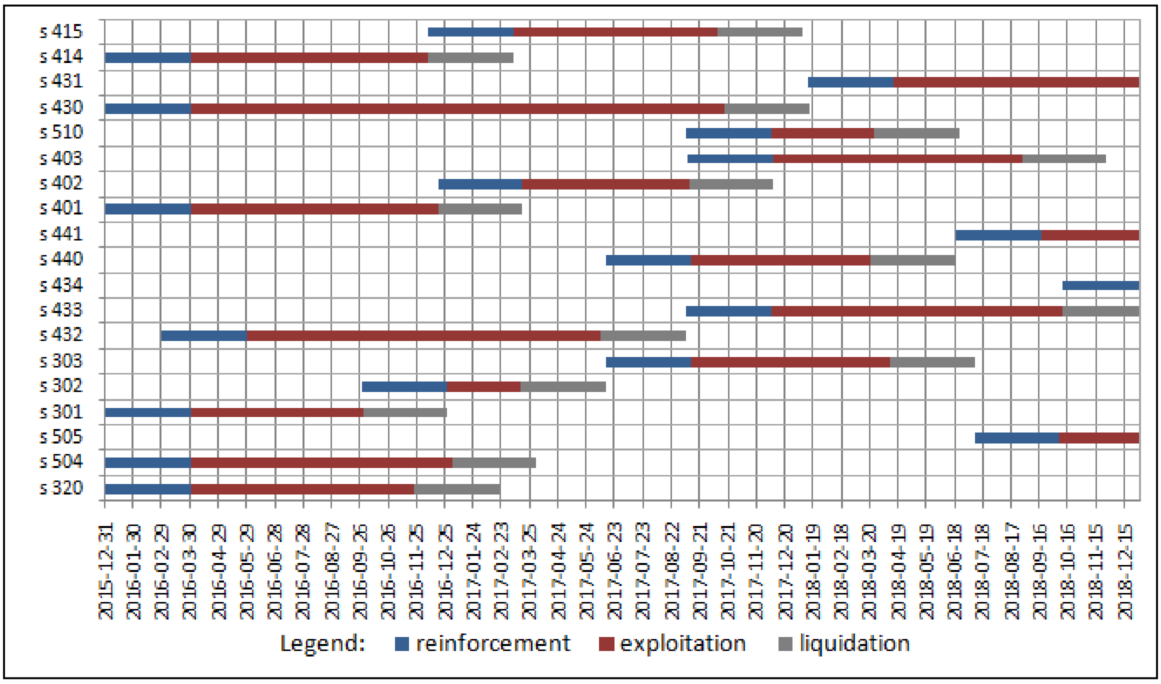

Fig. 5. A fragment of the optimal solution schedule
Source: Own study.

Conclusions

Optimisation of the coal production is complex and complicated due to conditions of mining process. In complex design problems analytic methods fail. In such cases heuristic methods with suitable application could be used.

The heuristic approach is often used to aid in quick estimates and preliminary design process. Evolutionary algorithms allow to take into account most of the problem constraints. They are inspired by the process of natural evolution. This technique is routinely used to generate useful solutions for optimisation or planning in various engineering problems.

Algorithm described in the paper, enables support the process of modelling and optimisation of production in coal mine (or group of mines) where underground mining method with longwall system is used.

In the paper the case study includes five coal mines of selected coal company was presented. The optimisation problem has concerned allocation of 10 longwall sets in 61 planned longwalls. As optimisation criterion the minimisation of the coal production deviation from planned values (300 000 Mg/month) in analysed period (24 months) was assumed. Satisfying results were obtained – the optimal solution with fitness function has a very good fit to the level of planned production (average mean error approx. 3500 Mg/month). Fragment of the optimal solution schedule was also presented.

The presented algorithm is implemented in OPTiCoalMine calculation service at Virtual Laboratory GridSpace2 (shared on the server ACK Cyfronet as a part of Polish Grid Infrastructure). The implementation of the developed algorithm into grid structures makes possible to optimise the complex problems related to underground coal production and provides short calculation time by access to great computational power.

The developed algorithm could be also used for the evaluation of design solutions in terms of proposals of deposit cut or determining the order of planned excavations with equipment selection.

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