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USE OF GENETIC ALGORITHM IN LAYOUT DESIGN

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Abstract: Within the design of production layout, the planners are often confronted with complex, sometimes conflicting demands and a number of restrictive conditions, which encourages their efforts to develop new, progressive approaches to the development of production layouts. The purpose of the innovative approaches in this field is to provide users with better, elaborated designs in less time, while they are able to implement various restrictive conditions and company priorities to the design. One of the ways is a use of metaheuristic algorithms by space solution optimisations of manufacturing and logistics systems. These methods have higher quality results compared to classical heuristic methods. Genetic algorithms belong to this group. Main goal of this article is to describe the Genetic Algorithm Layout Planner (GALP) that was developed by authors, and its experimental verification and comparison with results of the classical heuristic.

1 Introduction to layout design

Process of layout design requires data from construction and technological preparation of production. Data for the manufacturing and logistics systems design can be divided into two basic groups [1]:

- Numerical data - information about products, production processes and resources [2].
- Graphical data – represent visual display of individual elements of the manufacturing and logistics system which are used mainly in layout design, modelling and simulation of the resultant system.

When we know the need of individual resources of the designed system, material flows and other connections among individual elements, we can begin to design an ideal spatial arrangement of the manufacturing or logistics system.

Proposing an ideal arrangement is advantageous to use optimisation methods and algorithms, which can be classified as follows [3]:

- Graphical methods (Sankey chart, spaghetti diagram, relationship diagram, etc.);
- Analytical methods (linear and non-linear programming, transport problem, methods of dynamic programming, etc.);
- Heuristic methods that includes construction procedures (CORELAP, ALDEP, PLANET, MAT, MIP, INLAYT, FLAT, etc.), change procedures (CRAFT, MCRAFT, MULTIPLE, H63, FRAD, COFAD, etc.) and combined procedures (BLOCPLAN, LOGIC, etc.);
- Metaheuristic methods (genetic algorithms, simulated annealing, Tabu search, Ant Colony optimisation, etc.).

2 Genetic algorithms

Genetic algorithm (GA) belongs to one of the basic stochastic optimisation algorithms with distinctive evolutionary features. Nowadays, it is the most used evolutionary optimisation algorithm with a wide range of theoretical and practical applications [4,5].

General procedure of genetic algorithm:

1. Initialisation – creation of initial (zero) population, that usually consist of randomly generated individuals.
2. Start of a cycle - thanks to a certain selection method, a few individuals with a high fitness function are selected from a zero population.
3. New individuals are generated from selected individuals via the use of basic methods (crossover, mutation and reproduction), new generation is created.

4. Competence calculation of new individuals (fitness function calculation).
5. End of a cycle - decision-making unit:
   - as long as the finishing criterion is not completed, move on to the point no. 2,
   - if the finishing criterion is finished, algorithm is completed.
6. End of algorithm - individual with the highest competence represents the main algorithm output and the best possible solution found.

Selecting the appropriate presentation of a problem is the most important application part of genetic algorithm. In a case of genetic algorithm, space of real problem is transformed to space of strings. These could be for example bit-strings, which were one of the first used representations. Real-valued vector representation is most commonly used for practical issues. In case of direct spaces, integer vector could be selected.

Constant population size is regulated in two ways. It is a so-called generation model that replaces the whole population by offspring (via mutation or recombination). Second option is to keep one part of the previous generation. This is done by elite selection or in other words by individuals with the highest fitness function. By selecting this way, it is guaranteed that the competence of the best individual will continue to improve [6].

3 Integration of genetic algorithm into design process of manufacturing systems

Design approach of manufacturing disposition with use of genetic algorithms, proposed by authors from this article, requires realisation of the following basic phases [7,8]:

1. Preparation phase for the disposition arrangement proposal - preparation of numerical data for analysis and layout optimisation, graphical data for 2D and 3D model creation of manufacturing system.
2. Application phase of genetic algorithm - algorithm core - optimised block layout is its output. The core works in the following steps:
   - requirement specification and input value assigning for GA,
   - optimisation of space arrangement with GA use,
   - GA procedure conclusion.
3. Processing phase of designed disposition arrangement in CAD system - transformation of proposed block layout into detailed 3D model of manufacturing system.
4. Phase of proposed solution's static verification - verification of a proposed solution based on calculation and analysis of material flows.
5. Phase of proposed solution's dynamic verification - verification of a proposed solution with use of software simulation.

The next chapter of this article contains detailed description of phase 2, based on basic structure of used genetic algorithm and verification of algorithm functionality and comparison of achieved results with classical heuristics application.

4 Layout optimisation using genetic algorithm

Proposed genetic algorithm for layout optimisation consists of the following steps
(Figure 1):

- requirement specification and input value assigning for GA,
- core of GA - optimisation of space arrangement,
- GA procedure completion (finishing requirements).

4.1 Solution requirement specification and input value assigning

In first part of the solution it is necessary to define basic requirements for proposed manufacturing disposition. These requirements come from a previous phase of process and analysis of input data. For optimisation purposes and GA use it is necessary to set following parameters [9]:

- number of placed workplaces, machines and devices,
- mutual relations and intensity among workplaces,
- A,E,I,O,U,X coefficients for relation evaluation,
- ration of fitness function intensity and mutual relations,
- specification of entry-exit places of manufacturing system,
- specification of machines and devices,
- specification of hall dimensions and potential construction restrictions (walls, columns, corridors).

It is also necessary to set parameters of genetic algorithm as [10]:

- maximum number of generations (iterations),
- number of individuals (solutions) in generation,
- selection types, crossover and mutation of their probability,
- required value of fitness function (optional information),
- maximum solution time (optional information),
- maximum number of generations without solution improvement.

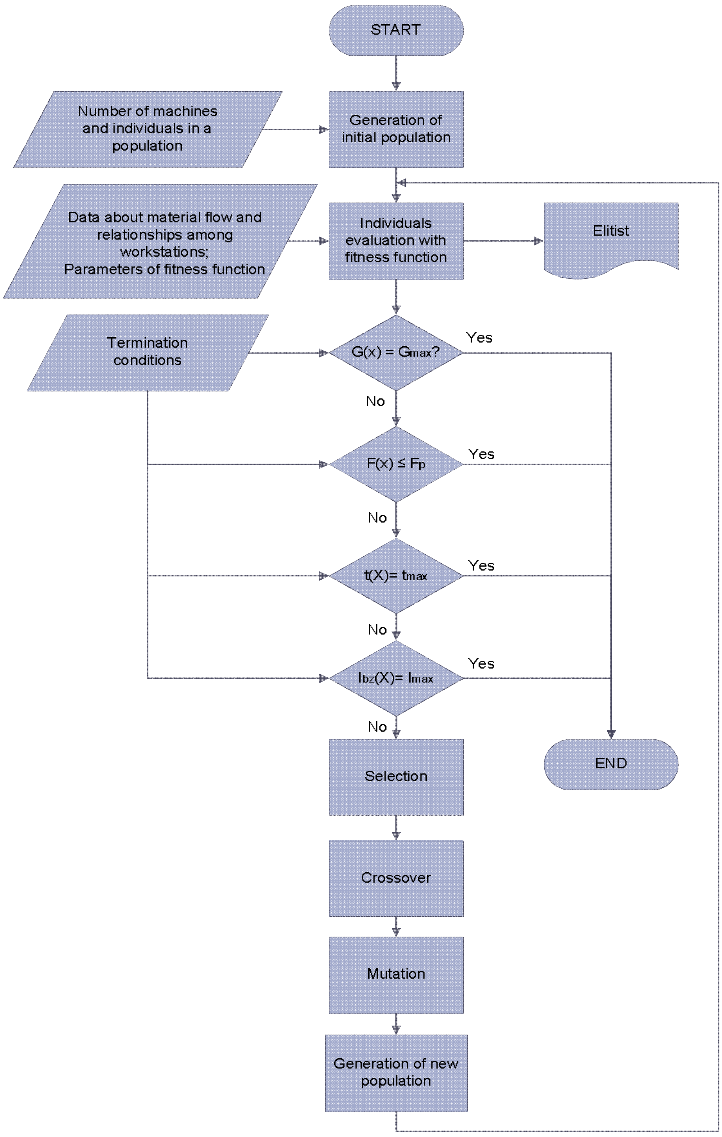

Figure 1 Own genetic algorithm for layout optimisation

4.2 *Optimisation of space arrangement using genetic algorithm*

After specification of all input data, own optimisation of space arrangement follows with the help of genetic algorithm. Basic parts of GA core will be explained in the following text.

1. Generation of initial population:

First step is to create a population that represents a group of solutions which will be further developed. In this solution, an individual is created by genes in the quantity that is equivalent to value of placed machines. These can have a value of 1 up to n, where n is equal to number of deployed machines. Sequence of individual genes corresponds with sequence where machines will be placed in the proposal. Next, there is one gene in each individual reserved for a pattern definition by which workplaces will be included in the proposal. Total matrix dimension corresponding to population in one generation, therefore [9]:

NUMBER OF INDIVIDUALS IN GENERATION × (NUMBER OF PLACED MACHINES + 1).

2. Individual evaluation of fitness function:

After having created a population, it is necessary to evaluate a fitness function. Resulting fitness function was designed as a sum of 2 components with verified weight. Verification was done according to the intensity of material flow and distance (fID) and according to relations and distance (fV).

Evaluation according to the intensity and distance (1) [10]:

$$f_{ID} = \sum_{i,j=1}^{i,j=n} D_{ij} \times I_{ij} \qquad (1)$$

Evaluation according to relations and distance (2) [10]:

$$f_V = \sum_{i,j=1}^{i,j=n} V_{ij} \times D_{ij} \quad \text{for } V_{ij} \geq 0 \; OR$$
$$f_V = \sum_{i,j=1}^{i,j=n} \frac{V_{ij}^2}{D_{ij}} \quad \text{for } V_{ij} < 0 \tag{2}$$

where:
n – number of placed machines,
D – right angle distance between workplaces i-j (D_ij=|x_i-x_j |+|y_i-y_j |),
I – intensity between workplaces i and j,
V – evaluation coefficient of a relation between workplaces i and j.

Final fitness function value (3) is set as:

$$\min: \; f = \alpha \times f_{ID} + (1-\alpha) \times f_V \tag{3}$$

where:
α - ratio coefficient of partial fitness functions (α ∈⟨0;1⟩).

Various restrictions are checked in layout construction and algorithm itself (overlapping objects, length, width and height of a production hall, transport street arrangement, position of fixed objects in a production hall, etc.).

After evaluating all individuals by a fitness function, the best solution is identified and saved in given generation - elite individual with his or her reached value and average value of fitness population. This data could be displayed during algorithm operation after each generation, in order to track solution progress. After completion, it is also possible to display a progress graph of average and elite fitness value.

3. Decision-making blocks:

In this step, it is necessary to compare specific conditions for algorithm termination in 4 decision-making blocks. Current solution state:

- To reach maximum number of generation (iteration) Gmax,
- To reach or exceed the highest permissible fitness value fp,
- To reach maximum solution time tmax,
- To exceed set iteration number (Imax) without improving of reached solution.

When meeting any out of four stated conditions, genetic algorithm is completed.

4. Selection:

In case none of the finishing criterion was fulfilled, the algorithm continues by selection, in other words by selecting individuals who will crossbreed and eventually mutate between each other. For such solution, roulette rule has been selected. Probability selection was proportional to an individual's achieved suitability. This form was chosen based on better possibility to search complex set of solutions when later combining parents and their evaluation as well as their calculation speed [11]. To prevent early convergence, suitability of individuals was integrated into algorithm via the help of sigma scaling.

After selecting, pairing follows, where Parent 1 and Parent 2 will be randomly selected from chosen individuals. These should make Offspring 1 and 2.

5. Crossover:

In order to prevent duplicate of identical machines in crossover or omission of same machines from genetic chain, mechanism of partially matched crossover was designed. This type of crossover has within its procedure implemented measures. These guarantee that each coded solution will have its machine only once [12].

6. Mutation:

After the crossover, mutation follows. However, in this type of solution encoding, traditional mutation or in other words value change of a random gene is out of the question. This would automatically require remedial measures to eliminate duplication or not classified machines. That is why mutation via the help of inversion or exchange was selected. Due to inversion rather big intervention into solution, probability was divided for exchange or inversion in 80:20 ratio [13].

7. Making of a new generation:

Following the genetic operator activity, parents are replaced by offspring. In case elitism is used in suitability evaluation and the best possible solution has been saved, this individual replaces one of the offspring with the worst suitability.

After this step, algorithm goes back to evaluating new individuals through the help of fitness function. Furthermore, algorithm keeps repeating in cycles until one of the finishing conditions is fulfilled [14].

8. Genetic algorithm finishing:

In decision-making blocks, each genetic algorithm cycle checks whether one of the finishing conditions has not been fulfilled:

- achieving the maximum number of generations (iterations),
- achieving or exceeding the highest permissible fitness value,
- achieving the maximum solution time,
- exceeding the set number of iterations without improvement.

If some of the finishing conditions were fulfilled, activity of genetic algorithm will finish. After completion of its activities there are generated outputs in user interface:

- block layout,
- achieved fitness value and information in which iteration was achieved,
- graph showing progress of average and elite fitness population values.

In the final phase, user will decide whether the solution proposed by genetic algorithm fulfilled all its requirements. If not, it is necessary to closely specify requirements and repeat generation of optimal layout. If requirements were fulfilled, methodology continues by result processing in CAD system.

5 Experimental verification of genetic algorithm and result comparison with use of classical heuristic

In order to check the functionality of the proposed GALP algorithm (Genetic Algorithm Layout Planner) series of experiments were carried out. These results were then compared with optimisation results with the help of heuristic according to Murat (sequence-pair approach). Heuristic according to Murat has been selected because it is believed the heuristic approach is implemented in Factory PLAN/OPT module, which is a part of software Siemens Tecnomatix. Final PLAN/OPT and GALP algorithm proposals were subsequently compared in FactoryFLOW software. A common characteristic for both algorithms is the block layout output. Both algorithms require finishing requirement and total time of algorithm functioning. For more complex result comparison, experiments were carried out for 1, 5, 10 and 20 minutes. Own experiments were carried out for 2 types of inputs:

- Case 1 - simple manufacturing system: 3 manufacturing families, 24 workplaces,
- Case 2 – complex manufacturing system: 9 manufacturing families, 60 workplaces.

Case 1 results are shown in the table 1. These experiment results indicate that GALP achieved better results in all cases than PLAN/OPT algorithm, which due to unknown reasons did not even keep workplace dimensions in some cases. GALP has also proposed solutions preferring singular direction of material flow with minimum crossing or backward material flow. Due to comparing both algorithms, no restrictions have been imposed on workplace arrangement. However, GALP algorithm enables basic restriction definition in the layout (production hall dimensions, height of spaces, material component arrangement, fixed installations or transport corridors in the layout).

Table 1 Experiment Result Comparison for Case 1

	Time calculation	GALP			PLAN/OPT		
		Distance (m)	Costs (EUR)	Time (min)	Distance (m)	Costs (EUR)	Time (min)
Achieved results	1 min	571 360.33	25 434.76	69 708.00	669 925.47	25 746.26	70 146.72
	5 min	510 552.24	25 023.22	67 682.66	633 664.26	25 668.70	70 281.26
	10 min	441 472.39	24 825.88	67 536.68	548 718.83	25 284.36	68 976.65
	20 min	430 341.00	24 755.86	67 214.88	529 770.15	25 214.38	68 811.54
Comparison GA – PLAN/OPT	Time calculation	Distance (m)	Costs (EUR)	Time (min)	Distance (%)	Costs (%)	Time (%)
	1 min	-98 565.44	-31.50	-438.72	-14.71	-1.21	-0.63
	5 min	-123 112.02	-645.48	-2 598.60	-19.43	-2.51	-3.70
	10 min	-107 246.44	-458.48	-1 439.97	-19.54	-1.81	-2.09
	20 min	-99 429.15	-458.52	-1 596.66	-18.77	-1.82	-2.32

Table 2 Experiment Result Comparison for Case 2

Parameter	GALP	PLAN/OPT	Difference	Difference (%)
Distance covered (m)	2 877 483.27	4 654 622.41	-1 777 139.14	-38.18
Costs (EUR)	83 939.38	91 344.13	-7 404.75	-8.11
Time (min)	230 818.14	253 032.38	-22 214.24	-8.78

Experiment results were consequently verified also taking into account complex solution of manufacturing system (Case 2) and solution time was set to 5.5 hour (solution time 1000 task generations in GALP). Advantages of genetic algorithm became evident in a more extensive problem. Final material flow is directed with minimum crossing. However, in case of PLAN/OPT algorithm, there is a crossing, where material flow keeps coming back and there is not any technology island creation in manufacturing system. Genetic algorithm proposed layout with greatly lower value of transportation performance (38.18%) than heuristic algorithm in a PLAN/OPT module. Experiment result comparison is stated in table 2.

6 Conclusions

The main aim of this article is to describe the use of genetic algorithm in manufacturing layout optimisation. The article describes the basic algorithm structure and its experimental verification. It also compares algorithm outputs of traditional heuristic application. Experiment results show the proposed GA provide saving of transport performance in case of less complex problems, which is 15-20% compared to classical heuristic results. When problem complexity increases, saving from the GA use continues to increase (Case 2 - saving more than 38%). Also, disposal arrangement generated by GA leads to a solution with easier and directed material flow. Proposed genetic algorithm is a part of complex project methodology of manufacturing dispositions and its basic steps are described in chapter 3. Furthermore, this proposed GA enables the user to consider practical restrictions when arranging space in layout optimisation, that is a shape and production hall dimensions (length, width and height) building block placement (e.g. columns), fixed installations, transport corridors, input and output spaces of manufacturing system, etc. Therefore, this means that layout that has been designed by a genetic algorithm requiring the minimum number of corrections that do not represent significant deviations from optimal parameters of material flows.

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References

[1] KRAJČOVIČ, M.: *Modern approaches of manufacturing and logistics systems design*, Digitálny podnik 2011, digitálny podnik - cesta k budúcnosti, 2011, Žilina: zborník prednášok, Žilina: CEIT SK, pp. 12, 2011. (Original in Slovak)
[2] KRAJČOVIČ, M., FURMANN, R.: Interactive system of production layout design, *Produktivita a inovácie: dvojmesačník Slovenského centra produktivity*, Vol. 10, No. 1, pp. 4-5, 2009.
[3] FUSKO, M., RAKYTA, M., MANLIG, F.: Reducing of intralogistics costs of spare parts and material of implementation digitization in maintenance, 12th International Scientific Conference of Young Scientists on Sustainable, Modern and Safe Transport Location 2017, *Procedia Engineering*, Vol. 192, pp. 213-218, 2017.
[4] BUBENÍK, P., HORÁK, F.: Proactive approach to manufacturing planning, *Quality Innovation Prosperity*, Vol. 18, No. 1, pp. 23-32, 2014.
[5] BACK, T.: *Evolutionary Algorithms in Theory and Practice: Evolution Strategies, Evolutionary Programming, Genetic Algorithms*, Oxford: Oxford University Press, 1995.
[6] GASOVA, M., GASO, M., STEFANIK, A.: Advanced industrial tools of ergonomics based on Industry 4.0 concept, 12th International Scientific Conference of Young Scientists on Sustainable, Modern and Safe Transport Location 2017, *Procedia Engineering*, Vol. 192, pp. 219-224, 2017.
[7] HYNEK, J.: *Geneticke algoritmy a genetické programování*, Praha: Grada publishing, a.s., 2008. (Original in Czech)
[8] WU, X., CHU, Ch.-H., WANG, Y., YAN, W.: *A* genetic algorithm for cellular manufacturing design and layout, *European Journal of Operational Research*, Vol. 181, No. 1, pp. 156-167, 2007.
[9] KRAJČOVIČ, M., HANČINSKÝ, V.: Production layout planning using genetic algorithms, *Communications: scientific letters of the University of Žilina*, Vol. 17, No. 3, pp. 72-77, 2015.
[10] HANČINSKÝ, V.: *Využitie evolučných algoritmov pri návrhu výrobných dispozícií*, dissertation thesis, Žilina, UNIZA, pp. 143, 2016. (Original in Slovak)
[11] RAJASEKHARAN, M., PETERS, B.A., YANG, T.: A genetic algorithm for facility layout design in flexible manufacturing systems, *International journal of Production research*, Vol. 33, No. 1, pp. 95-110, 1998.
[12] KRAJČOVIČ, M., BULEJ, V., SAPIETOVÁ, A., KURIC, I.: Intelligent Manufacturing Systems in concept of digital factory, *Communications: scientific letters of the University of Žilina*, Vol. 15, No. 2, pp. 77-87, 2013.
[13] RISTVEJ, J., ONDREJKA, R., ŠIMÁK, L., LOVEČEK, T., HOLLÁ, K., LACINÁK, M., ŠURINOVÁ, L., JÁNOŠÍKOVÁ, M.: *Simulation Technologies in Risk Prevention within Crisis Management*, Modelling and Simulation 2016 - European Simulation and Modelling Conference, ESM 2016, EUROSIS, pp. 327-330, 2016.
[14] PERISA, M., PERAKOVIC, D., VACULIK, J.: Adaptive Technologies for the Blind and Visual Impaired Persons in the Traffic Network, TRANSPORT, Vol. 30, No. 3, pp. 247-252, 2015.

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