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Simulation-based Flexible Layout Planning Considering Stochastic Effects

Dávid Gyulai[a,b,*], Ádám Szaller[b], Zsolt János Viharos[a,c]

[a]Fraunhofer Project Center at Institute of Computer Science and Control, Hungarian Academy of Sciences, Kende str. 13-17, H-1111 Budapest, Hungary
[b]Department of Manufacturing Science and Engineering, Budapest University of Technology and Economics, Egry J. str. 1, H-1111 Budapest, Hungary
[c]Kecskemét College, Izsáki road 10., H-6000 Kecskemét, Hungary

* Corresponding author. Tel.: +36-1-279-6181; fax: +36-1-466-7503. *E-mail address:* david.gyulai@sztaki.mta.hu

Abstract

Layout planning is an important practical problem for manufacturing companies. In today's market conditions —characterized with continuously changing product portfolio and shortening product lifecycles— frequent reconfiguration is requested if the primary goal for the company is to remain competitive. The key to win customers is to widen the product portfolio and customize the products, however, this leads to the problem that the manufacturing system has to be re-organized several times during its life cycle that requires solving design problems frequently. In the paper, a novel layout planning method is introduced that can be applied efficiently to solve real industrial problems. The method applies automated simulation model building to create the different layouts. It focuses on minimizing the objective function that is specified according to the pre-defined key performance indicators (KPI). The solution is a hybrid optimization method, in which evaluation of the layout alternatives is done by simulation and the improvement of the solution is performed by a near-to-optimal search algorithm. The optimization is separated from the simulation model in order to boost the computations. Important advantage of the solution is the efficiency consideration of stochastic parameters that improve the applicability of the results.

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Keywords: manufacturing plant layout planning; stochastic analysis; simulation; near-to-optimal optimization

1. Introduction

1.1. Background and motivation

Practical layout planning problem is often faced by companies when extending the production capacities (e.g. new plant or facility is built), introducing new products in their portfolio or modifying available manufacturing resources. The latter two cases are more frequent, as competitive markets and changing customer requirements ask for continuous innovation, new technologies, processes and products. Although flexible and reconfigurable production systems offer efficient solutions to manage both internal (new products) and external changes (change in the volumes), they need to be applied in the right way to exploit their advantages. Besides the management of these systems, the design of the entire facility is also needed to efficiently utilize the flexible approaches.

The above requirements lead to the practical problem of layout planning, which stands for the physical allocation of production facilities and equipment (e.g. machines, workplaces) on the shop-floor. The complexity of the layout planning problem is generally inherited from several factors that need to be considered to take the right decisions. Logistics related objectives include the minimization of the transportation routes, besides, the layout needs to match the production-related requirements like the availability of the material, maximal utilization of the machine resources and lowest possible work-in-progress (WIP). While respecting all the above mentioned aspects of the layout planning problem, the production system evaluation calculations cannot be performed by considering ideal parameters —like deterministic processing times and order arrivals— but a robust solution is needed that is able to perform well even in a dynamic environment with random events and stochastic parameters.

Therefore, the proposed, novel layout planning method is aimed at calculating the near-to-optimal layout while considering stochastic factors that are relevant in the industrial practice. The method relies on the discrete-event simulation (DES) model of the considered production system, and the layout is planned applying search heuristics, by iteratively evaluating layout alternatives. The structure of the paper is as follows. First, the review of the relevant literature and the state-of-the-art layout planning methodologies are listed and evaluated, then the general layout planning problem is specified by the consid-

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ered parameters and the related boundaries. Next, the proposed simulation optimization workflow is introduced by the description of the coupled simulation model as well as the search heuristics. The efficiency of the proposed method is justified by experimental results, then outlook and future steps are detailed.

1.2. State-of-the-art in layout planning

Layout planning and optimization has an extensive literature: based on the different objectives and constraints various different approaches exist to solve the assignment problem. An extensive review in the topic was introduced by Singh, highlighting that facility layout planning is a well-studied combinatorial optimization problem, which can be defined as finding the most efficient arrangement of n indivisible facilities in n locations [1]. As for the classification of the different layout planning problem alternatives, Drira et. al presents a comprehensive study, in which the emerging problems are characterized according to different criteria [2]. The authors highlight that workshop characteristics regarding the facility shapes and dimensions, as well as the product volume and variety leads to different problem formulations and thus various solutions.

Considering the product portfolio of the company, both variety and volume affects the characteristics of the problem, as the applied production system type basically relies on these factors. Thus, one can distinguish among cellular, process- and product-oriented systems that ask for different modeling approaches. Besides, characteristic of the problem is the configuration of the layout, which stands for the general arrangement scheme of the resources. In this classification, single-, multi-row, open-field and loop layout categories exist, and different constraints and formulations are required to represent these arrangements in the planning models. Next to the characteristics of the considered production environment, the layout model and the solver algorithm are also important elements of the planning problem. In general, layout planning is modeled in four different formulations: quadratic assignment [3], graph theoretic model [4], mixed-integer programming model [5] and stochastic optimization problem [6], which models induces directly the set of applicable solver algorithms. In the paper, the latter formulation is preferred to represent the practical layout planning problem, and to capture the actual, stochastic nature of the important parameters. Most formulations (quadratic assignment, mixed-integer) of the layout planning problem are $\mathcal{NP}$-complete by nature, therefore optimal solution cannot be obtained by polynomial-time algorithms [7]. Moreover, if stochastic parameters are considered, the problem becomes even more complex thus it can be solved only by heuristics, search metaheuristics and stochastic optimization methods.

As for the search metaheuristics, simulated annealing (SA), and evolution methods like genetic algorithm (GA) are applied in most of the cases. In case of well-tuned parameters and good evaluation functions, these methods able to provide good solutions in reasonable running time, even in case of complex problems. These metaheuristics often serve as a basis to implement more efficient but problem type specific heuristics. In layout planning, well-known successful heuristics are *CLASS* (SA-based, [8]), *SABLE* (SA-based, [9]), *LOGIC* (GA-based, [10]) or *FACOPT* (SA and GA, [11]). Besides the above described approaches, fuzzy and graph theory approaches are also applied successfully to solve the layout planning problem. Different perspective in the layout planning problem is the time-representation, which introduces novel constraints and objectives, as well as complexity in the problem. Nowadays, production systems must be react quickly on the changes in the product portfolio and/or customer order stream, therefore the time factor is important, in case the evolution of the facility is also considered in the layout planning problem. Dynamic layout planning problems are aimed at optimizing the arrangement of the shop-floor equipment over multiple-periods, considering the above mentioned changes, whereas static problems apply a single planning period. Another aspect of layout planning is the design level, in this case one can distinguish between plant and cell levels of which the latter is considered in the paper.

2. Problem statement

2.1. General characteristics of the layout planning problem

Having the classification factors and model formulation alternatives defined in the previous section, the general characteristics of the layout planning problem considered in the paper is summarized as it follows. The layout planner of a company has to arrange a given set of machines in a two-dimensional (z dimension is disregarded here) space in order to minimize the costs that incur when producing a given set of products. Accordingly, the layout planning can be classified as a single period problem, or it can be considered as a problem whose time period is continuous. It means that the planner respect the fluctuation of the individual orders in time, and does not arrange the machines considering only cumulated volumes and order stream data.

The task is to arrange a set of machines (with different sizes and functions) on the shop-floor by harmonizing the layout with the production of the quasi-random order arrivals. There are different product types with specific routings and processing time, and individual customer orders, each of which corresponds to a single product. The boundaries of the shop floor are given, as well as the inbound and outbound logistics positions that specify the arrival (input) and exit (output) points of the material flow on the layout. Besides the walls of the factory hall, further physical constraints of the layout planning problem are the columns that are arranged in raster-like pattern on the shop-floor (representing e.g. pillars of the production hall or any other restricted areas). The machines can be arbitrarily arranged on the floor respecting the physical constraints, however, pattern-like arrangement is preferred for easier realization considering production management and logistics processes. Not only the positions but also the orientations of the machines are respected and optimized in the proposed approach. As introduced in the previous section, important aspect of the layout planning is the representation of the stochastic parameters and random events in the formulated model, therefore, a detailed specification of the problem is provided in Section 2.2.

2.2. Boundaries and specification of the problem in question

In the considered benchmark layout planning problem, machines need to be placed and arranged on an L-shaped shop-floor with the dimension of 18×30 meters and a 5×20 meters idle corner area. Physical constraints of the placement are the pillars, which are equally distributed in the hall with a 5×5m raster. In the considered problem, ten machines (M1-M10) need to be placed with the following dimensions:

- 1m×2m: 2 pieces (M1, M2)
- 2m×3m: 2 pieces (M3, M4)
- 3m×4m: 4 pieces (M5-M8)
- 4m×5m: 2 pieces (M9, M10)

Customer orders concern to six different product types, the order arrivals are represented by normal distribution with a mean value of 600 seconds and a standard deviation of 210 seconds. The order creation is done according to the arrival frequency and quantity (the total volume of each product types) summarized in Table 1. The processing times of the different product types are summarized by Table 2. The above specifications aim to give a representation of the stochastic nature of any real production assignments incorporating distributions in process times, order arrival intervals and amounts.

Table 1. Frequency, volume (for order creation) and routing of the products.

Prod.	Freq. [%]	Total vol. [pcs.]	Routing
P1	10	300	M1-M2-M3-M4
P2	15	450	M2-M5-M6-M8
P3	25	750	M8-M9-M10
P4	10	300	M2-M6-M7-M8-M9-M10
P5	15	450	M1-M5-M9
P6	25	750	M1-M2-M3-M4-M5-M6-M7

Table 2. Processing time of the product on different machines.

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
P1	600	116	750	380	0	0	0	0	0	0
P2	0	650	0	0	450	885	525	449	0	0
P3	0	0	0	0	0	0	0	0	216	1380
P4	0	600	0	0	0	715	325	400	775	600
P5	1000	0	0	0	272	0	0	0	355	0
P6	700	210	900	75	150	280	665	0	0	0

3. The proposed solution

As mentioned in Section 1.1, a discrete event simulation based method is proposed to solve the layout planning problem. Discrete event simulation is widely used in the evaluation of production and logistics processes, as it enables the fast evaluation of different dynamic systems. The key advantage of the simulation against the optimization methods is that the stochastic events can be handled much easier. However, a simulation model is not capable of optimizing the system configuration, but it can only evaluate the performance of it. For fast and effective decision support the two techniques are often combined, which is called simulation-supported optimization [12]. This approach can be efficiently used to solve real industrial problems, since —in case of appropriate parameterization— it accelerates finding the optimum by orders of magnitude [13]. The substance of the method is that the results provided by the optimization algorithm are evaluated by the simulation model, and then fed back to the input of the optimization algorithm, forming an iterative process. It results in a technique that combines the benefits of both techniques, namely the possibility of optimization and the fast evaluation which takes into consideration the stochastic processes [14]. The developed method applies automated model building, which means that simulation model parameters can be changed by modifying them in an external data table, without modifying the simulation model itself.

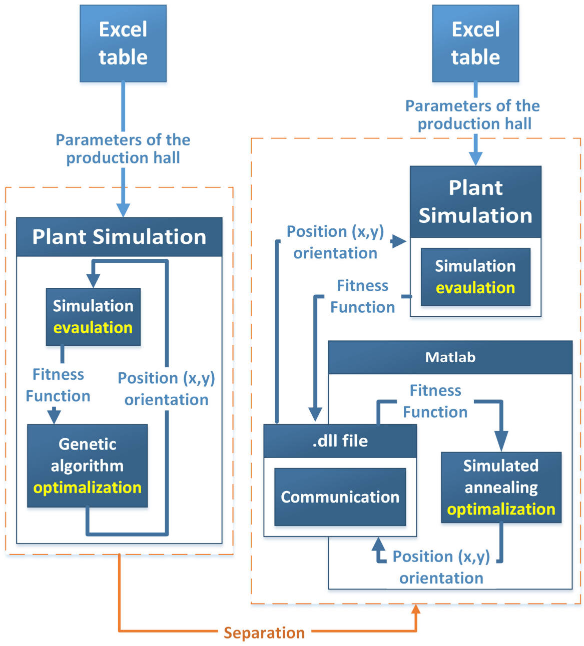

Fig. 1. Workflow of the simulation-supported layout planning.

In the research, two search metaheuristics were tested: genetic algorithm and simulated annealing. The simulation model was implemented in *Technomatix® Plant Simulation*, which offers a built-in genetic algorithm. For simulated annealing, the simulation model and the optimization had to be separated: the simulation model communicated with a pre-written *Matlab®* simulated annealing function through a *.dll* file (Fig. 1). To calculate the goodness/fitness of a given layout, a fitness function (FF) was defined, which is the sum of the following KPI-s, multiplied with different weights:

- *Overlapping:* sum of the areas where the machines overlap with other objects (e.g. columns) or with each other (its target value is zero for the final optimal solution).
- *Line Length:* total length of the routes which connect the machines (transportation length aspect).
- *Lead time (average):* The time that a product spent in the production system (transportation, waiting and processing).
- *Utilization:* average of the machines' utilization.
- *WIP:* average work-in-progress during the simulation.

The search algorithms are minimizing the FF, consequently all the KPI-s have to be minimized, except utilization, which has negative weight. The decision variables are the position coordinates (x,y) and the orientation (four cases, rotation with 90°) of the machines. The coordinates correspond to the center of the machines, the values can run between $0 \dots 18$ (x) and $0 \dots 30$ (y) according to the size of the production hall. Thus, the machines can extend over the borders of the hall, which is penalized by the *Overlapping* KPI. The parameters of the search algorithms are adjusted during test runs and the following were set for the experiments:

1. Genetic algorithm
   (a) Number of iterations: 1000
   (b) Population size: 30
   (c) Probability of mutation/crossover/inversion: 0.1/0.8/0.1
2. Simulated annealing
   (a) Number of iterations: 6000
   (b) Initial temperature: 1000
   (c) Generating new points: The step has length temperature, with direction uniformly at random.
   (d) Annealing function:

$$\frac{\text{initial temperature}}{ln(\text{number of actual iteration})} - 115.67 \qquad (1)$$

The annealing function is given by the Boltzmann-formula, with a 115.67 reduction. The modification was necessary because the temperature was not low enough in the last iterations, the algorithm took larger steps in the last iterations. In simulated annealing, if the new objective function value is less than the old, the new point is always accepted. Otherwise, the new point is accepted at random with a probability depending on the difference in objective function values and on the current temperature. The acceptance probability is the following [15]:

$$\frac{1}{1 + \exp\left(\frac{\Delta}{\max(T)}\right)} \qquad (2)$$

4. Experimental results

4.1. Comparison of the algorithms

Both algorithms were tested on the same problem instance introduced in Section 2.2. As mentioned, the purpose of the analysis was to investigate the effect of the stochastic parameters on the solution of the planning. A sample solution is depicted by Fig. 2, if the 25% deviation is set for the processing times. Twenty-one experiments were made with genetic algorithm and with simulated annealing: the deviation of the machines' manufacturing times in the percentage of its expected value were increased from 0% to 100% with 5% step size. The algorithms calculated near-optimal layout in each experiment, the values of the FF are illustrated by Fig. 3. With GA, the average running time of the experiments was 2.5 hours, in the case of SA this value is 2 hours[1]. If a linear trend line is fitted on the results, it can be observed in what manner the achievable smallest FF value is growing with increasing the deviation of the manufacturing time. It is also represented that the relation between the process time distribution and the solution's FF value do not have a linear or other specific trend, but a highly non-linear correlation that cannot be calculated in a general

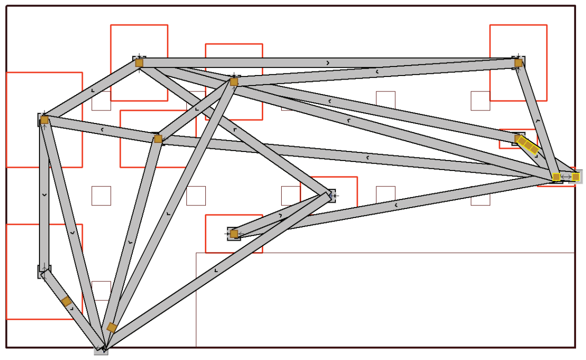

Fig. 2. A sample layout without route optimization, resulted by GA in case of 25% deviation is considered.

production environment directly. The difference between the FF values are occurred by the parametrization in several cases, however, fine tuning of the parameters may decrease these differences. First, the extreme values are always caused by some overlaps in the final layout (only in the experiments with SA). One of the main purposes is to avoid these to create a realizable layout, thus the weight of overlapping in the FF should be further increased.

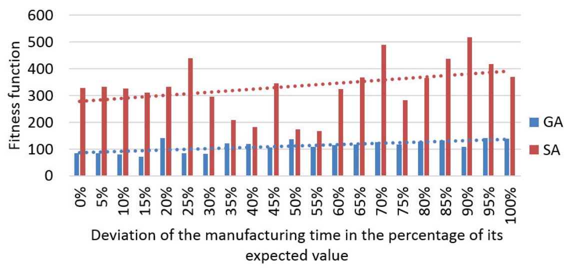

Fig. 3. Comparison of the results of genetic algorithm and simulated annealing.

4.2. Conclusions of layout planning using genetic algorithm

Based on the experiments, it can be concluded that the change of the FF value is caused by the decrease of the utilization. In the final layouts it can be observed that the machines form groups near the arrival and exit points to decrease the line length KPI (Fig. 2). An important question is the sensitivity of the solution on the changes of the process times distribution. It was analyzed in what manner a re-optimization on a given stochastic distribution gives better solution than using the optimal layouts of three selected distributions (0%, 35%, 65%, 100%). Therefore, different resulted layouts which are calculated with the specific deviation value are compared from the viewpoint of how much are they effective, if the deviation of the manufacturing time is changed. On the optimal layout for 0%, 35%, 65% and 100% deviation 10 experiments were performed with each deviation value ($4 \cdot 21 \cdot 10$ experiments). The FF was calculated in each case, and the averages of the 10 experiments are shown in Fig. 4. It can be concluded that for each layout, almost always that model is significantly better which is parametrized accordingly the specific deviation value, the average advantage is 20% considering the total fitness values. Thus,

[1] All the computational experiments presented in the paper were performed on a laptop with 8GB RAM, and Intel® Core i7 CPU of 3.1 GHz, and under Windows 8.1 64 bit operating system.

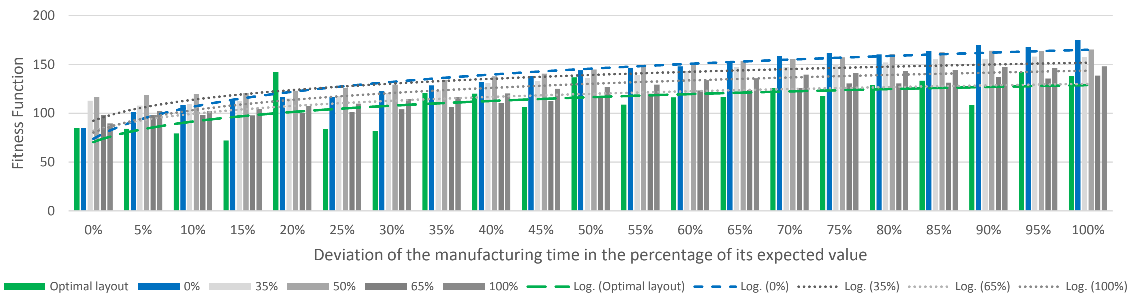

Fig. 4. Comparison of the final layouts created with different deviation values of manufacturing time.

if the deviation values are known in advance, it is worth to run the simulation according to the specific deviation value. This fact represents positive outcome since the proposed algorithm is able to find optimal shop-floor layouts in various production circumstances but also it is a drawback, *as the changes in the stochastic parameters of the manufacturing assignments during the life cycle of the plant requires re-optimization of the given layout.*

4.3. Conclusions of layout planning using simulated annealing

The search algorithms were also compared and evaluated in the proposed solution methodology. While the layout calculated with GA could be improved with increasing the number of iterations, the main challenge with SA is to eliminate the opportunity of stopping in a local optima. Local optima points lead to extremely high FF values (Fig. 3). In the layouts created with using SA (in order to reach better results, the algorithm was run repeatedly), the machines form groups in the center of the production hall, which leads to the growth of all KPI-s, except the utilization. The average utilization of the machines is smaller than that of the layouts planned with GA, but also show a decreasing tendency. The other KPIs do not change significantly the deviation of the manufacturing time changes, but their values are greater in total.

5. Conclusions

The paper introduced an integrated, simulation-based, near-to-optimal optimization framework for shop-floor layout planning. *Special analysis was carried out to analyze the impact of stochastic effects —arising in manufacturing environments— on the resulted optimal system layout, and on the production performance parameters. The proposed framework takes into account the physical constraints (e.g. walls and columns) of the given plant and also any other so called restricted areas defined by the system layout planner, and finds the optimal (horizontal and vertical) position of the machines together with their best orientation inside the available area.* The physical entry and exit positions of the products are also defined by the planner. Using the simulation model, detailed performance evaluation of a given configuration is performed, by executing a manufacturing scenario including orders with stochastic arrival and processing times and given routings. Transportation times inside the plant are calculated considering the actual positions and distances of the resources, moreover bypass times of restricted areas are also taken into account. Each resource has an entry puffer to avoid waiting components on the transportation routes. The performance KPIs of a given manufacturing layout considers transportation efforts, average lead time, utilization of the production resources and the average WIP level. A special KPI during the optimization process is the overlapping area of resources with each-other and with any other restricted physical areas of the physical production plant, however, this KPI has to reach always zero value at the end of an optimization run.

The proposed optimization methodology was analyzed on a typical, benchmarking production plant layout with a comprehensive set of stochastic orders and resources, with relatively complex routings and varying, stochastic processing times. The aim was to define a complex and general layout optimization assignment. Special analysis was done focusing on the correlation between the varying distributions of manufacturing processing times and the system performance with the resulted optimal layout. The results show that *it is worth to re-design a production system layout when the distribution of processing times at the resources are changing that is far not a typical behavior of our todays manufacturing control and management.* The losses in KPIs were also calculated avoiding these re-design steps (20% in average). These results mirrored a direct link between local, low-level machine production times and the global, plant level architecture of manufacturing systems. The outlook in the next paragraph defines the planned, further improvement steps of the research, including the integration of a shop-floor network route planning method.

6. Outlook

6.1. Shop-floor route network planning

The current solution considers the shop-floor transportation efforts through an estimation of the route lengths, however, it is not a transportation route planning method, therefore the route planning comes after the final optimal layout for the position of the machines is resulted (Fig. 2). Solving the layout-planning problem, an important step is to place the routes between the machines (or manufacturing cells), however, there are several factors that need to be considered in route-planning.

Once, it has to be adapted to the defined layout —being only as simple as necessary— to ensure a realistic transportation among the machines. Simple means that usually horizontal and vertical directions are applied in today's plants, the existence of skew routes are rare exceptions. It is not negligible that the created routes have to be positioned as close as possible to the machines. In this initial state, a pre-calculation is made after each simulation run. This calculation is practically a k-means clustering algorithm, which defines the positions of the horizontal and vertical routes by assigning the machines to them (to the closest route), depending on the orientation of the machines.

To avoid the increase of simulation time and complexity, the routes in our approach are straight, and take place from wall-to-wall in the production hall. Therefore, two clustering operations are performed: one for the horizontally oriented machines (it calculates the position of the vertical routes), and one for the vertically oriented machines (it calculates the position of the horizontal routes). The question is how many clusters are required? *It was observed during the experiments that the machines form groups in the environment of certain coordinate values in both directions*, the number of clusters is equal to the number of groups. The result of the solution of the clustering algorithm is shown in Fig. 5 (squares symbolize the machines). The output of the calculation are the coordinates of the routes: the simulation model creates them according to the results of the clustering algorithm (Fig. 5). The developed method defines the position of the routes after placing the machines optimally, and the goal is to integrate these two algorithms: extend the FF with a new part (which depends on the evaluation of the created route network) and calculate the FF after the route-planning. In some cases, the routes cross the machines, this also need to be corrected in the future.

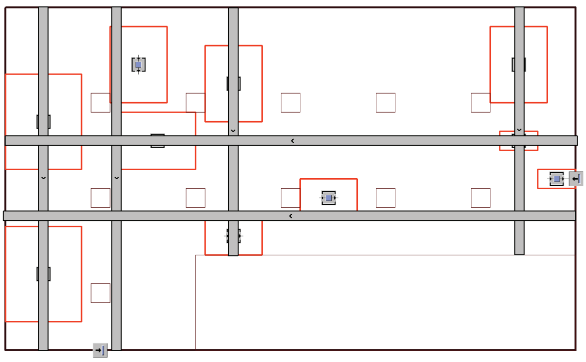

Fig. 5. Visualization of the clustering with routes in the simulation model.

6.2. Future work

The future work of the research is summarized in the following points:

- The running time of the layout planning algorithm can be significantly reduced replacing the time-consuming simulation with iteratively trained neural networks as in the pioneering work of the authors [16].
- Other search algorithms can be tried out to improve search efficiency. Thanks to the introduced Matlab-simulation connection, using Matlab various optimization techniques can be chosen and analyzed (and combined) besides simulated annealing easily.
- The layout planning method can be tested on other benchmarking types of production halls: since it uses automated model building, only the data stored in the Excel table has to be changed.

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