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MULTI-CRITERIA SCHEDULING OF ORDER PICKING PROCESSES WITH SIMULATION OPTIMIZATION

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Abstract

In profit-oriented environments, such as warehousing in the automotive industry and its suppliers, the minimization of labour costs, and thus the flexibility of labour force is an increasingly important issue. Such an operating policy requires effective capacity planning methods to determine the number of personnel and equipment per activity and scheduling procedures to define the sequence of tasks by considering their strict deadlines. In the following, the use of a discrete event simulation model for multi-criteria scheduling optimization of order picking activities in an automotive parts warehouse with genetic algorithm (GA) is presented. The operative planning system consists of a database, a discrete event simulation model, an application for capacity estimation and a scheduling algorithm. The system was designed to support operative warehouse management personnel in order to pick process scheduling and planning.

Keywords: simulation, genetic algorithms, scheduling, order picking.

1. Introduction

The flexibility of labour in a warehouse means that available personnel are redeployed during shifts to activities (storage, order picking, replenishment, etc.) where extra capacity is required. In the case when available labour capacity is not sufficient, temporary staff can be hired from specialized agencies.

Order picking – retrieval of products from storage to meet customers' demand – is often the most labour-intense activity in a warehouse. The human hand as a 'handling equipment' is hard to be replaced and economical automation of retrieval of products is seldom possible. Therefore, the costs of order picking may amount to about half of the operational costs in a warehouse, so any improvement in this field may result in significant cost reduction (Van den BERG [9], ROODBERGEN [6]).

2. The Order Picking Process

2.1. Planning and Disposition

Based on the customers' orders, the operative planning of the order picking process in a *Warehouse Management System* (WMS) is completed in the following steps (Ten HOMPEL and SCHMIDT [8]):

1. Download of customers' orders from the Host system;
2. Separation of orders into one-unit and multi-unit orders;
3. Appointment of the pick position of each product;
4. Drawing up internal orders (pick lists) based on the external (customers') orders;
5. Calculation of the number of empty pallets needed per pick list;
6. Determination of the retrieval (lead) time of each pick list;
7. Disposition of resources to each pick list by considering different constraints.

2.2. Retrieval of Products

A so called *picker-to-part* order picking method is implemented in the presented planning system. The order pickers receive information about their next task at a designated location (depot) in the warehouse. First they drive their pallet truck to pick an empty pick device (pallet). Then the order pickers ride along the pick positions in the aisles of a multi-block warehouse. The order pickers pick the proper quantity manually from the lowest level of the racks to the pallet on the truck. Following each pick, they confirm the action and then they read information about the next pick location. When the pick device is full or the picking list is completed, the pickers ride to the area of the warehouse where the shipments are controlled and prepared before loading them on the trucks. After dropping off the pick device the pickers return to the depot to receive the next task (GUDEHUS [3], TARNAI [7]).

3. The Model

The object of the developed model is to determine on the one hand the number of order pickers, on the other hand the sequence of the retrieval of the pick lists so that the total cost of order picking is minimal. The objective function describing the optimization problem consists of the following three terms (KLJAJIĆ [4]):

- Minimization of the labour costs;
- Minimization of earliness/tardiness costs;
- Maximization of resource utilization.

The labour costs are determined by the number of order pickers and the specific labour costs which may vary per each shift. The pick lists must be ready for shipping by the internal deadlines calculated by the tour-planning module of the WMS based on delivery dates of the customers' orders. Deviation from these cut off times induces incidental expenses.

If the orders are prepared earlier, then these must be stored temporarily, so storage costs occur and in addition, useful space is occupied from other warehousing activities. However, if the trucks must wait because the orders are not picked on time, then transports may arrive late to customers, service level of delivery declines and extra labour and other costs may occur.

In order to convert the objective function into a minimization problem, the maximization of resource utilization is formulated as the minimization of idle times. Idle times refer to the times when order pickers do not work during the shift and they are not taking a rest but have no task to perform.

The objective function (O) can be described in the following discrete form:

$$O = [\Sigma_i (P_i * C_{Li}) * \alpha] + [(E * C_e + T * C_t) * \beta] + [(I * C_i) * \gamma], \qquad (1)$$

where

O:	the total cost of order picking in the planning time horizon;
i:	number of shifts;
P_i:	number of order pickers in shift i;
E:	total time of earliness;
T:	total time of tardiness;
I:	total idle time of pickers;
C_{Li}:	labour cost of a picker in shift I;
C_e:	the unit time earliness penalty (cost);
C_t:	the unit time tardiness penalty (cost), in practice, generally $C_t > C_e$;
C_i:	the unit idle time penalty (cost);
α, β, γ:	weights of the three terms in the objective function;

The warehouse management sets are the C_{Li}, C_e, C_t and C_i values based on the contracts with the customers, and the statistics from the controlling system. All three terms' dimension is monetary unit [USD, EUR]. The warehouse management also sets the weights (α, β, γ) of the three terms of the objective function. These weights reflect the individual importance of each term in the company's long term strategy.

The model determines the optimal sequence of the completion of the pick lists in three phases:

- Experiment;
- Estimation;
- Optimization.

In the first phase the time needed to pick each list is evaluated. Based on the mean times, the number of required order pickers is estimated for each shift. In the third phase, the optimal schedule can be produced (*Fig. 1*). In the following, the three phases of the model are described.

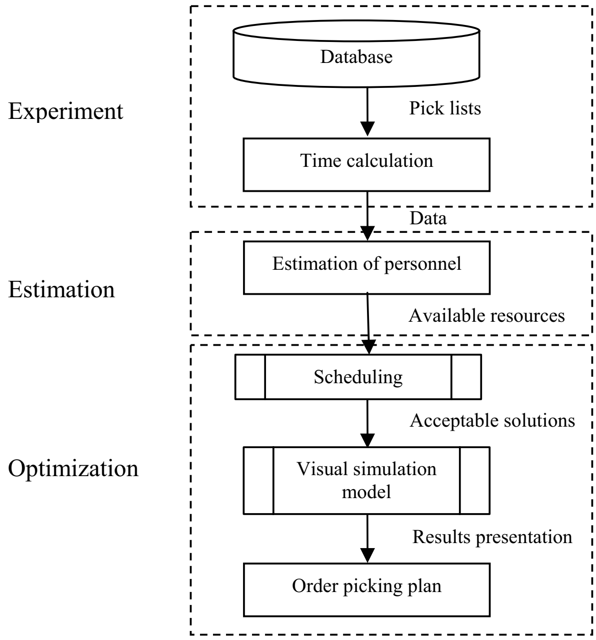


Fig. 1. Scheduling and decision support process for order picking planning

3.1. Experiment

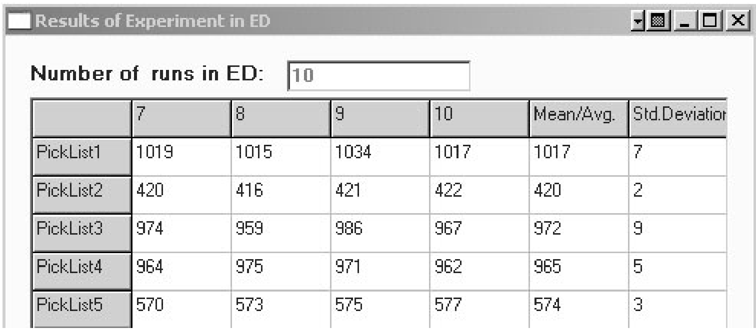
The model supports the last two steps of the operative planning of the order picking process described previously, so it is assumed that the pick lists are already produced. The lists must contain the ID number, the pick location and the pick quantity of each stock keeping unit (SKU) on the list, and the deadline of completion. The lists are processed in tab delimited file (.txt) format in order to make the system independent from the type of the database in which the lists are stored.

To simulate order picking processes, the times needed for:

- preliminary activities,
- picking up and dropping off loads,
- acquisition of information, recording of data,
- concluding activities (fastening of the load etc.),

and the physical properties, the speed and acceleration values of the applied equipment must be analysed. For validation purposes and to handle the changes in the performance of the order pickers, the stochastic of the activities, the structure of the shifts, and to complete planned experiments the model was implemented in Enterprise Dynamics 5.1, a visual interactive modelling and animation simulation package.

In the *Experiment* phase, the retrieval time of each and every list is measured separately. The number of measurements is a variable set by the user. The results – the single time values, the average and the standard deviation of times measured – of an Experiment of 10 runs with 5 pick lists are shown in *Fig.* 2.



	7	8	9	10	Mean/Avg.	Std.Deviatior
PickList1	1019	1015	1034	1017	1017	7
PickList2	420	416	421	422	420	2
PickList3	974	959	986	967	972	9
PickList4	964	975	971	962	965	5
PickList5	570	573	575	577	574	3

Fig. 2. Results of the *Experiment* phase

3.2. *Estimation*

A good order-picking schedule means good resource utilization while respecting cut off times and other constraints in the warehouse (pauses during the shifts etc.). Based on the deadline of completion, the lists are sorted into shifts. In this phase the deadlines inside the shifts are not taken into consideration. The application – developed in the Delphi programming environment – estimates the number of order pickers needed per shift so as to complete all lists during the given shift by the most balanced load on the pickers. The input of the application is the result table of the *Experiment* phase with the average retrieval times of the pick lists. The output of the *Estimation* phase is shown on Gantt charts.

3.3. *Optimization*

The change of the management interest from productivity improvement to inventory reduction, the introduction of information technologies that enable it, and the emergence of new management philosophies like Just-in-Time (JIT) production, demand warehouses to deliver lower volumes but more frequently with shorter response times from a significantly larger assortment of products.

As a result of these trends, the number of customer orders has increased and the punctuality of deliveries has become essential. Since the complexity of the scheduling problem grows factorially with the number of tasks to be carried out, traditional methods are not able or consume too much time to find a suitable solution.

Constraint programming (CP) is a technique to solve non-linear problems, mostly in planning and scheduling. The problems are solved by imposing constraints and choosing an appropriate search strategy. Genetic algorithms are proven search methods with good quality/speed ratio (GOLDBERG [2]).

4. Genetic Algorithm

Genetic algorithms represent the solutions of a problem by a set of parameters. These parameters are regarded as the *genes* of a *chromosome*, and a set of chromosomes is named *population*. In case of permutation problems, the best representation technique is to use the indexes of the tasks in the permutation, and so one chromosome is a sequence of integer numbers (DERHÁN [1]).

The chromosomes of the GA in the Optimization phase represent the order in which the pick lists are released to the order pickers to be retrieved from storage. *Fig. 3* shows the logic of the optimization with GA.

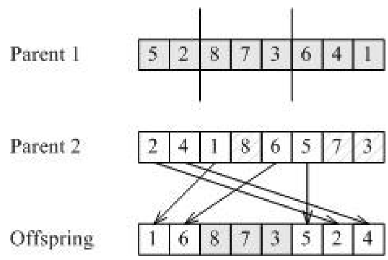


Fig. 3. Optimization with GA

The GA prepares an initial population (1^{st}) of chromosomes based on the data extracted from the database. The number of genes in a chromosome is equal to the number of pick lists in the scheduling problem. The number of the chromosomes in each population is fixed and may be set by the user at the beginning of the scheduling. With the help of the simulation model, the objective function of each chromosome in a generation is evaluated. Based on the objective function values, the fitness of each member of the given generation is calculated. According to their fitness, parent chromosomes are selected and they form an offspring with GA operators, like crossover and mutation. The offspring is placed in the new (n^{th}) generation.

Offspring are created until a new generation is not complete. The new generated population is used in the further run of the algorithm. The creation of new populations is repeated until the end condition is not satisfied. From the last generation the best solution is returned.

The programme for scheduling optimization was developed in the Delphi programming environment, and for the evaluation of the objective functions, the model in Enterprise Dynamics 5.1 – described in the Experiment phase – was used.

The simulation model evaluates each chromosome in a population separately, calculates the time difference between the cut off time and the actual finish time of every pick list and stores the idle time of the pickers.

The objective value O (see chapter 3.) is mapped into a fitness value F, by the Power Law Scaling method, where the actual fitness value is taken as a specific power (k) of the objective value (MAN [5]):

$$F_i = (O_{\max} - O_i)^k + O_{\min}, \tag{2}$$

where

O_i: objective value of chromosome i
$O_{\max}$: the largest objective value in the population
$O_{\min}$: the smallest objective value in the population
F_i: fitness value of chromosome i
k: constant, set by the user ($k \geq 1$).

The selection technique selects two parents at a time and employs the Roulette Wheel Mechanism (MAN [5]). After selecting two parents, the Offspring is formed by applying the Order Crossover (OX) technique, described in *Fig. 4*. In case of Order Crossover one randomly selected segment (8,7,3) from Parent 1 is copied to the same place in the Offspring. The remaining empty positions in the Offspring are filled from Parent 2, by keeping the sequence but skipping the already used points.

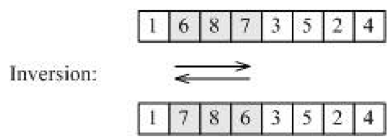


Fig. 4. Order Crossover

The Offspring is mutated with a mutation probability – which also can be set at initialization – using the Inversion mutation technique (*Fig.5*). This method inverts the genes between two randomly selected segments of the chromosome.

The chromosomes created with the GA operators after selection are added to the new population. Elitist selection is the other method to add chromosomes with high fitness to a new population. The principal of elitism is that a user set parameter determines the number of the fittest chromosomes from the population which are selected and placed in the new population without any manipulation. When the new population is complete, the previous population is replaced and the search for the solution continues.

When the end condition is fulfilled, the algorithm stops the search process. The result is the sequence of the pick lists in which they should be released to the floor to achieve the best solution by considering all of the predefined constrains.

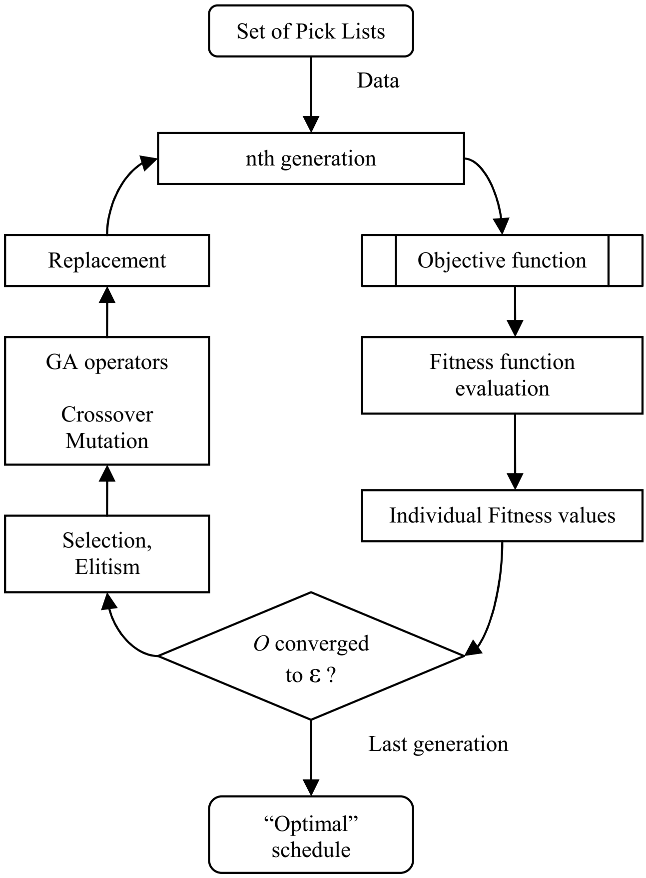


Fig. 5. Inversion Mutation

5. Order Picking Process Scheduling and Planning

As mentioned in the *Estimation* phase, the number of pickers is evaluated per shift, based on the total number of pick lists but only partially considering their final deadline. It is also stated that good scheduling means good resource utilization while respecting constraints of the order picking process. To achieve good resource utilization, the number of pickers evaluated in the Estimation phase must be tested and – if necessary – refined.

The model's feature is that the number of pickers per shift is not a fixed number but can be varied in an interval. The middle of the interval is the number of pickers defined in the Estimation phase, and the radius can be set by the user. The default value of the radius is 1, which means, in case of an estimated number of 5 pickers in a shift, the model will also evaluate the scenarios, when 4 and 6 pickers are working in the given shift. If there are three shifts in a warehouse in a day, and for each shift three different size of personnel are there to examine, that means all together 27 possible scenarios.

The model evaluates all the possible scenarios separately and searches for the best sequence of the pick lists. When the best solution for each scenario has been determined the results are presented to the user. As the output of the model, the operative warehouse management personnel receive the following data per scenario:

- Number of order pickers in each shift
- Best sequence of the pick lists returned by the Genetic Algorithm
- Total labour cost
- Total cost of earliness/tardiness and idle times

Based on these data, the operative warehouse management personnel can decide the number of order pickers to be deployed per shift to retrieve orders from the warehouse. For every scenario, the best sequence of fulfilment of the pick lists is presented. By analysing the costs, the management can decide if they undertake the risk of preparing some orders later than the deadline determined by the tour-planning module of the WMS or employ more order pickers with higher labour costs, if necessary.

6. Conclusion

Both optimization and simulation are tools that support decision making. Optimization uses fixed input data, avoiding uncertainty and details. Optimization models simplify the complexity of the real system and some factors are even not considered. The simulation is not creative like optimization, but can cover uncertainty and complexity of dynamic systems in detail.

The combination of optimization and simulation (simulation optimization) can be defined as the process of finding the best set of input variables without evaluating each possibility. The objective of simulation optimization is to minimize the resources spent (i.e. time) while maximizing the quality of information gained in the experiment.

The model represented in this paper also uses the benefits of simulation optimization. The designed system supports operative warehouse management personnel in order to pick process scheduling and planning. By evaluating a number of scenarios, the number of the order pickers per shift, and the best sequence of releasing the pick lists to be retrieved from storage are determined.

It is the management's responsibility to monitor and control the order picking activities in the warehouse continuously and force the adherence to the schedule. If all order picking activities are realized according to the schedule, then the planning of the replenishment of the order picking places is also possible. The goal of the author of this paper is to further develop the above described planning system and include the scheduling of these activities, too.

The connection to the database of the WMS with the simulation model already exists so it is possible to determine when the last products will be picked from each picking place and when replenishment is necessary. By applying advanced search methods – like Genetic Algorithms – the optimal schedule for the replenishment of the picking places can be evaluated. The objective function must reflect the goal of planning the replenishment process so that the order picking processes can be executed continuously and undisturbed – products are available at the picking place and the congestion in the aisles is avoided.

It is also the object of further development to improve the optimization algorithm and reach higher speed and accuracy in calculation. In this first version of the model, all probabilities to execute each genetic operator were constant. The proposed development will operate with variable probabilities for crossover and mutation to inherit the properties of the fittest individuals into the next population, to avoid premature convergence and to close-up the search space.

References

[1] DERHÁN, D., *Optimalizáló eljárás készítése genetikus algoritmus alkalmazásával*, M.S. thesis, Budapest University of Technology and Economics, 2002.
[2] GOLDBERG, D. E., *Genetic Algorithms in Search, Optimization & Machine Learning*, Addison Wesley, 1997.
[3] GUDEHUS, T., *Logistik 2*, Springer Verlag, Berlin, 1999.
[4] KLJAJIĆ, M. – BERNIK, I. – BRESKVAR, U., Production Planning Using Simulation Model and Genetic Algorithms, in: *Proceedings of the IASTED International Conference*, Marina del Rey, CA, USA, May 13–15 (2002), ACTA Press, Anaheim, pp. 54–58.
[5] MAN, K. F. – TANG, K. S. – KWONG, S., *Genetic Algorithms, Concepts and Design*, Springer Verlag, Berlin, 1999.
[6] ROODBERGEN, K. J., *Layout and Routing Methods for Warehouses*, Ph.D. thesis, Erasmus University, Rotterdam, 2001.
[7] TARNAI, J., A raktári komissiózó rendszerek fejlesztése, *Anyagmozgatás – Csomagolás*, **45** (6) (2000), pp. 8–11.
[8] TEN HOMPEL, M. – SCHMIDT, T., *Warehouse Management*, Springer Verlag, Berlin, 2002.
[9] VAN DEN BERG, J. P., A Literature Survey on Planning and Control of Warehousing Systems, *IIE Transactions*, **31** (1999), pp. 751–762.