IIE Transactions (1999) **31**, 751–762

A literature survey on planning and control of warehousing systems

JEROEN P. van den BERG*

Faculty of Mechanical Engineering, University of Twente, P.O. Box 217, 7500 AE Enschede, The Netherlands
E-mail: j.van.de.berg@berenschot.com

Received December 1997 and accepted November 1998

We present a literature survey on methods and techniques for the planning and control of warehousing systems. Planning refers to management decisions that affect the intermediate term (one or multiple months), such as inventory management and storage location assignment. Control refers to the operational decisions that affect the short term (hours, day), such as routing, sequencing, scheduling and order-batching. Prior to the literature survey, we give an introduction into warehousing systems and a classification of warehouse management problems.

1. Introduction

1.1. *The increasingly busy warehouse*

Gudehus [1] and Graves [2], Hausman [3] and Schwarz [4] introduced the design, planning and control of warehousing systems as new research topics. The operation of warehousing systems has received considerable interest in the literature ever since.

It is not surprising that the research on warehousing systems gained interest in the 1970s, since this was the era that management interest shifted from productivity improvement to inventory reduction. The introduction of information systems made this strategy possible, with *Manufacturing Resources Planning* (MRP-II) as a notable example. From Japan a new management philosophy emerged: *Just-In-Time* (JIT) production. JIT attempts to achieve high-volume production using minimal inventories of parts that arrive just in time. These new developments demanded from warehouses that low volumes be delivered more frequently with shorter response times from a significantly wider variety of *Stock Keeping Units* (SKU's). The new interest in quality forced warehouse managers to re-examine their warehouse operation from the viewpoint of minimizing product damage, establishing short and reliable transaction times and improving order-picking accuracy.

Current trends in warehousing and distribution logistics are *supply chain management* and *Efficient Consumer Response* (ECR). Supply chain management and ECR pursue a demand-driven organization of the supply chain with small inventories and reliable short response times throughout the supply chain. All deliveries are driven by the sales downward in the supply chain. Such an organization requires a close cooperation among the companies in the supply chain and the immediate feedback of sales data. Nowadays, information technology enables these developments through Electronic Data Interchange (EDI) and software systems such as the MRP-based *Enterprise Resources Planning* (ERP) systems and *Warehouse Management Systems* (WMS).

The new market forces have affected the operation of warehouses tremendously. On the one hand, they demand an increased productivity. On the other hand, the rapidly changing market imposes financial risks upon the introduction of capital intensive high-performance warehousing equipment which may be difficult to re-configure or discard. Hence, there is a great need for sophisticated techniques that provide a dependable basis for adequate planning and control of warehouses in such complex environments.

In this paper we present a survey of methods and models that have appeared in the literature for the planning and control of warehousing systems. In the remainder of Section 1, we discuss warehousing systems and warehouse management. In Sections 2 and 3 we discuss the literature on planning and control issues, respectively. Finally, in Section 4 we end with conclusions and suggestions for future research.

1.2. *Warehousing*

Warehousing involves all movement of goods within warehouses and *Distribution Centers* (DC's), namely:

---

*Current address: Berenschot, P.O. Box 8039, 3503 RA Utrecht, The Netherlands. Tel.: +31302916822, Fax: +31302916826

0740-817X

receiving, storage, order-picking, accumulation and sorting and shipping. An *order* lists the SKU's and quantities requested by a customer or by a production unit, in a DC or a *production warehouse*, respectively. *Order-picking* is the process of gathering SKU's that have been requested in an order at one time.

In an order-picking operation, the order pickers may pick one order at the time (*single order-picking*). A higher efficiency may be achieved by picking multiple orders simultaneously (*batch picking*). Furthermore, orders may be picked from separate warehousing systems or separate *zones* within systems. Consequently, in such situations the orders need to be sorted and accumulated to establish order integrity. Orders may be sorted during the order-picking process (*sort-while-pick*) or afterwards (*pick-and-sort*).

Warehousing systems may be classified into three groups:

(1) Picker-to-product systems.
(2) Product-to-picker systems.
(3) Picker-less systems.

In a *picker-to-product system*, manual order-pickers ride in vehicles along the pick positions. There is a wide variety of vehicles available from manually propelled vehicles to motorized vehicles which also enable vertical movement for order-picking from elevated positions. Instead of a vehicle, a system may also include a take-away conveyor for picked products (*pick-to-belt*).

Examples of *product-to-picker systems* are the *Automated Storage/Retrieval System* (AS/RS) and the *carousel*. An AS/RS is a high-bay warehouse with *Storage/Retrieval* (S/R) *machines* or automated stacker cranes that perform the storage and retrieval of storage modules (such as pallets or containers). A *miniload* AS/RS is an AS/RS especially equipped for the storage and order-picking of small items. A *carousel* consists of storage positions that rotate around a closed loop thereby delivering the requested SKU's to the order-picker. Carousels may rotate horizontally (horizontal carousel) or vertically (vertical carousel).

Picker-less systems make use of robot-technology or automatic dispensers.

With respect to product retrieval we distinguish *unit-load retrieval systems* and *order-picking systems*. In a unit-load retrieval system complete unit-loads are retrieved. Accordingly, the vehicles either perform one stop (storage or retrieval) or two stops (storage followed by a retrieval) in a single trip. We refer to these trips as a single-command cycle and a dual-command cycle, respectively. In an order-picking system typically less-than-unit-load quantities are picked, so that there will be multiple stops per trip (multi-command cycle).

1.3. *Warehouse management*

We may establish high quality solutions for warehouse management by decomposing the task into a number of hierarchical subproblems. A well-defined hierarchy will prevent local optimization without considering the global context.

A broad hierarchy of management decisions is the following ([5]):

- Strategic decisions.
- Tactical decisions.
- Operational decisions.

Strategic management decisions are long-term decisions and concern the determination of broad policies and plans for using the resources of a company to best support its long-term competitive strategy. Tactical management decisions primarily address how to efficiently schedule material and labor within the constraints of previously made strategic decisions. Operational management decisions are narrow and short-term by comparison and act under the operating constraints set out by the strategic and tactical management decisions.

The central themes of this survey are planning and control of warehousing systems. Planning of warehousing systems refers to the policies which are developed at the tactical level concerning the assignment of goods to storage locations. Control problems concern the actual sequencing, scheduling and routing of the movement of goods.

Planning and control decisions are subject to strategic management and inventory management. Strategic management defines long-term goals and it constitutes the supply chain organization and the warehouse design (for a review of warehouse design models we refer to Ashayeri and Gelders [6]). Inventory management decides which products are kept in storage in what quantities and when shipments arrive.

Intelligent inventory management may reduce the inventory levels and thereby improve the efficiency of the warehouse operation. For a review of inventory models that consider the total inventory quantity we refer to Hariga and Jackson [7]. Since these models both involve the inventory and the warehouse operation, the models establish a bridge between the field of warehousing and the field of inventory management.

Since strategic decisions affect a long period, these decisions face high uncertainties. Typical methods used for solving such problems are stochastic models and simulation, based on demand estimates. Planning problems concern the intermediate period and consider an existing situation. Planning algorithms are based on historical data and attempt to find solutions with a high quality *average* performance. Control algorithms are based on actual data and attempt to find solutions with a high-quality performance. Combinatorial optimization techniques are well suited for solving planning and control problems. Case studies have shown that considerable productivity improvements are possible by applying intelligent planning and control policies [8–10].

2. Planning of warehouse operations

In this section we focus on the storage location assignment problem at the tactical level. The procedures that are developed at this level, serve as a framework for the actual location selection for incoming goods. In these procedures, the behavior on the intermediate term is estimated by historical demand patterns. Since the storage location assignment problem will be intractable as a whole, we introduce the hierarchical four step *Storage Location Planning Procedure*.

Storage Location Planning Procedure

1. Distribution of products among warehousing systems.
2. Clustering of correlated products.
3. Balancing of workload within warehousing systems.
4. Assignment of products to storage locations.

We discuss relevant literature on the successive steps in Sections 2.1 to 2.4.

2.1. *Distribution of products among warehousing systems*

Most large warehouses contain more than one type of warehousing system. Each warehousing system is especially equipped for a specific group of products based on their characteristics, such as: size, weight, shape, perishability, volume, demand rate, pick sizes, delivery quantity, type of storage module, *et cetera*.

Furthermore, many warehouses use separate systems or areas for order-picking (forward area) and for bulk storage (reserve area). Whenever a product in the forward area has been depleted, it is replenished from the reserve area. A well-known forward-reserve configuration is a storage rack where the lower levels are used for manual order-picking (forward area) and the higher levels contain the bulk storage (reserve area).

Bozer [11] treats the problem of splitting a pallet rack into an upper reserve area and a lower forward area. The author assumes Chebyshev travel times (i.e., the travel time of the pallet truck is the maximum of the isolated horizontal and vertical travel times) and a fixed pick-life for all unit-loads in the forward area. He shows when a separate reserve area is justified. He also studies the case with variable unit-load sizes and a remote reserve area. He analytically derives the break-even value for the pick-life of a unit-load, which is of potential use in deciding which products to consider for the forward area.

Hackman and Rosenblatt [12] present a model where order-picking from the reserve area is possible. Accordingly, the question arises which products should be picked from the forward area and how much space must be allocated to each of these products. The objective is to minimize the total costs for order-picking and replenishing. The authors assume that one replenishment trip suffices to replenish a product, irrespective of the allocated quantity. The authors derive analytic expressions for the optimal product quantities as a function of the available storage space. They present a knapsack-based heuristic that assigns these quantities to the forward area in sequence of decreasing cost savings until it is full. Frazelle *et al.* [9] incorporate the heuristic into a framework for determining the optimal size of the forward area. The costs in the model for order-picking in the forward area and for replenishing are related to the size of the forward area. Furthermore, they impose a congestion constraint and show its redundancy. Clearly, a model that minimizes the activity in the forward area, may well minimize the congestion at the same time. They prove that the procedure in Hackman and Rosenblatt [12] gives an optimal solution to the continuous relaxation of the problem. Finally, Frazelle *et al.* [9] present a case study where they project a 20% saving on labor cost by re-sizing the forward area down to 32% of its original size and by re-allocating the products among the forward and reserve area.

Van den Berg *et al.* [13] consider a warehouse with busy and idle periods where reserve-picking is possible. Their model allows advance replenishments during idle periods to reduce the replenishment activity during subsequent busy periods. This not only increases the throughput during the busy periods, it also reduces congestion and accidents. Contrary to the above publications, van den Berg *et al.* [13] consider a situation (e.g. pallet storage) where only one load is replenished per trip. The authors present a knapsack-based heuristic with a tight performance guarantee that attempts to find an allocation of products to the forward area that minimizes the total expected amount of work related to order-picking and replenishing during a busy period. Experiments with random data show savings may be possible of up to 30% in comparison with procedures used in practice.

2.2. *Clustering of correlated products*

In many warehouses there are certain products that often are ordered together. We will refer to such products as *correlated products*. We may reduce travel times for order-picking by storing correlated products close to each other in the warehouse (*correlated storage*). Obvious examples of correlated products are: components from the same supplier or items of the same color or size.

Correlated products may also be identified from historical data. Frazelle and Sharp [14] present a simple rule for identifying correlated products from a given order set. They perform a simulation study of a Miniload AS/RS where correlated products are stored together in the same bins. They report reductions of 30–40% in the number of retrieval trips.

Lee [15] presents a clustering procedure for an order-picking operation with man-aboard S/R machines. The procedure first creates clusters of correlated products. Next, it provides a sequence of the clusters and the products in the clusters according to increasing *Cube-per-Order Index*, COI (The COI is defined as the storage volume divided by the turnover rate of a product). Subsequently, it one by one assigns the products to storage locations following a space filling curve. Finally, an exchange routine attempts to improve the solution. Accordingly, the procedure both considers order structure and frequency. The decomposition approach presented by Lee [15] seems promising, although the procedure for clustering the correlated products looks arbitrary and lengthy.

Rosenwein [16] formulates the problem of clustering correlated products as a p-median problem. The cluster median is the product that has the highest correlation with the other products in its cluster. The p-median problem is the problem of finding p clusters with the highest correlation with the cluster *medians*. This problem may be solved optimally with a branch-and-bound algorithm. The authors report that the algorithm may solve a typical problem within 1 minute. However the model formulation, which includes the calculation of the correlation coefficients, is lengthy. An effective p-value is estimated from a travel distance approximation function.

Van Oudheusden *et al.* [8] present a case study of a warehouse operation with man-aboard S/R machines. Beside several other improvements, they introduce correlated storage. They generate clusters of two correlated products that are to be assigned to opposite storage locations in the aisles so that these can be accessed by the order-picker in a single stop. The problem of finding a pairing that minimizes the number of stops is polynomially solvable as a Weighted Matching Problem. A simulation study based on real data shows a 46% reduction in travel time when assigning correlated products to opposite storage locations. Van Oudheusden and Zhu [17] consider the problem of clustering correlated products for a person aboard S/R machine in an operation with a limited number of *recurrent orders*. These are orders containing the same lines that are requested on a regular basis. They present a dynamic programming heuristic that assigns the products in to storage locations based on the recurrent orders. The algorithm seems useful in situations where there is little overlap among the orders. If the overlap among orders increases, a clustering heuristic seems preferable.

2.3. *Balancing of workload within a warehousing system*

In many operations, order-pickers are dedicated to zones to reduce congestion and travel time. In such situations we may increase the throughput capacity by distributing the (clusters of) products among the zones such that the mean and peak workload are balanced among zones. Likewise, in an AS/RS with multiple aisles an an S/R machine in each aisle, we may improve the capacity of the system by distributing the workload evenly among the S/R machines. We are not aware of any publications discussing this issue with respect to warehousing.

2.4. *Assignment of products to storage locations*

The Storage Location Assignment Problem (SLAP) concerns the assignment products to storage locations. Such an assignment establishes a framework for allocating incoming loads to storage loactions. Hausman *et al.* [3] present three storage location assignment policies: randomized storage, class-based storage and dedicated storage. The randomized storage policy allows products to be stored anywhere in the storage area. The *class-based storage* policy distributes the products, based on their demand rates, among a number of classes and for each class it reserves a region within the storage area. Accordingly, an incoming load is stored at an arbitrary open location within its class. Under the dedicated storage policy each location may only be used for a specific product. Randomized and dedicated storage are in fact extreme cases of the class-based storage policy: *randomized storage* considers a single class and *dedicated storage* considers one class for each product. Class-based storage and dedicated storage attempt to reduce the mean transaction times for order-picking by storing products with high turnover at locations that are easily accessible. Randomized and class-based storage are also known as *shared storage* policies, for these allow the successive storage of units of different products in the same location.

2.4.1. *Unit-load retrieval systems*

In this section we consider storage location assignment in unit-load retrieval systems. The expected travel time for single-command travel is the cross-product of the turnover rates of the products and the single-command travel times to the locations to which these are assigned. Hardy *et al.* [18] show that the cross-product of two series is minimized if one series is non-increasing and the other is non-decreasing. The demand for a product may be estimated by the COI (cf. Section 2.1). Goetschalckx and Ratliff [19] introduce the *duration of stay* for individual loads as an alternative to the COI. The authors study an ideal situation and remark that the actual implementation of their approach in real warehouses still needs to be resolved.

Hausman *et al.* [3] introduce the cumulative demand function $G(i) = i^s$, where $i \in [0, 1]$ denotes a fraction of the products which contains the products with the highest COI and s is a suitably chosen parameter ($0 < s \leq 1$). Thus if 20% of the products generates 80% of all demand, then we find $s = 0.139$. For such a demand function $G(i)$, the authors show that a class-based storage policy with relatively few classes yields mean travel times that are close to those obtained by a dedicated storage policy. Graves *et al.* [2] extend the work of Hausman *et al.* [3] by also considering dual command cycles. With analytic computations using a continuous rack and discrete computations using a rack with 30 × 10 locations, they determine the expected cycle times for various combinations of storage policies, sequencing strategies and queue lengths of storage and retrieval requests. They observe further travel time reductions when allowing dual command cycles.

Schwarz *et al.* [4] verify the analytic results in Hausman *et al.* [3] and Graves *et al.* [2] with simulation. The simulations suggest that most results of the analytic models hold under stochastic conditions. The authors apply the *closest open location* rule for selecting a storage location under the randomized storage policy. It appeared that for a space utilization of 90% or more, the mean travel times with the closest open location rule are comparable to the analytic results for the mean travel time based on arbitrary location selection.

Hausman *et al.* [3] assume that the acceleration of the S/R machine is instantaneous. Due to this assumption and the fact that the S/R machine has independent drives for horizontal and vertical travel, the travel time of the S/R machine may be measured by the *Chebyshev metric*. Thus if Δx and Δy denote the translations in horizontal and vertical direction, respectively, and v^x and v^y denote the maximum speeds in the horizontal and vertical direction, respectively, then the associated travel time is $\max\{\Delta x/v^x, \Delta y/v^y\}$. The Chebyshev metric is also known as the *maximum metric* or the L_∞-*norm*. Guenov and Raeside [20] observe in their experiments that an optimum tour with respect to Chebyshev travel may be up to 3% above the optimum for travel times with acceleration/deceleration. Hwang and Lee [21] provide a travel time measure that includes acceleration/deceleration. Chang *et al.* [22] consider a travel time model with acceleration/deceleration and various travel speeds. In both papers, expressions are derived for the expected single and dual command travel time in an AS/RS for the respective travel time measures. We remark that a reasonable approximation of the actual travel time might be obtained with the Chebyshev metric, if a fixed extra travel time due to acceleration/deceleration is added per travel. The authors do not consider this option in their comparisons.

Hausman *et al.* [3] consider the problem of finding class regions for the class-based storage policy. The authors suggest *L-shaped* class regions (Fig. 1). This shape is optimal for Chebyshev travel times, if only single command cycles occur. Hausman *et al.* [3] analytically determine optimal class sizes for two classes in a square-in-time rack, such that the mean single command travel time is minimized for the demand function $G(i)$. The method assumes a continuous rack, i.e., individual rack locations are not identified. A grid search is used to determine optimal boundaries for three classes. Rosenblatt and Eynan [23] present a method for establishing class boundaries for any given number of classes in a square-in-time rack. Eynan and Rosenblatt [24] extend this method to any rectangular rack. All methods assume a continuous rack and the same demand function $G(i)$ as in Hausman *et al.* [3]. Graves *et al.* [2] observe that L-shaped regions are not necessarily optimal when dual commands occur. However, they argue that an L-shaped class allocation will in general be no more than 3% above the optimum, with respect to the mean dual command cycle time.

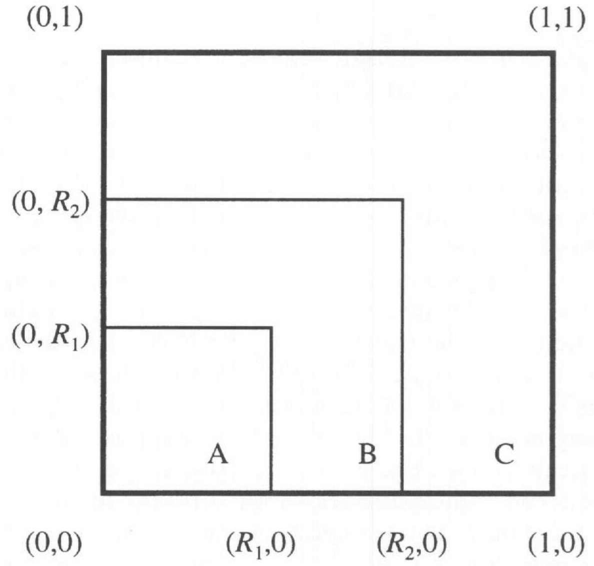

Fig. 1. L-shaped class allocation in a square- in-time rack with three regions and coordinates in time.

Graves *et al.* [2] observe that in order to enable an incoming load to be stored in its class region, the space requirements increase with the number of classes. Accordingly, class-based storage requires more rack space than randomized storage and dedicated storage requires more rack space than class-based storage. This effect was not accounted for in their computations, so that travel time reductions for dedicated storage and class-based storage may be overestimated.

Van den Berg [25] presents a polynomial time dynamic programming algorithm that distributes products and locations among classes such that the mean single command travel time is minimized. The algorithm may be applied to a wide variety of warehousing systems, since it holds for any demand curve, any travel time metric, any warehouse layout and any positions of the input station and output station. The algorithm allows that the inventory level varies and determines the storage space requirements per class by imposing a risk-level on stock overflow.

2.4.2. *Order-picking systems*

In this section we consider storage location assignment in order-picking systems. Jarvis and McDowell [26] consider an order-picking operation in a parallel aisle warehouse where order-pickers may access the entire warehouse area. The authors make the assumption that an order-picker traverses the entire aisle, upon entering the aisle. In an optimal storage assignment, the SKU's with the highest COI's fill up one aisle, the SKU's with the next highest COI's go to the next aisle and so on. If the I/O station is positioned at the end of the center aisle, then the aisles closest to the center should carry the SKU's with the highest COI. This allocation is known as the *organ pipe arrangement*. If the I/O station is not positioned symmetrically, then an iterative procedure is used to assign the aisles. The authors remark that the proposed storage assignment propagates congestion between order-pickers.

Guenov and Raeside [27] consider class shapes for order-picking in one aisle using a man-aboard S/R machine. They consider an instance with three class regions and tours with up to 30 picks. In all cases the class partition appeared to affect the travel time. The L-shaped class partition could be improved by aligning the class regions along the direction of travel when the crane simultaneously travels with maximum horizontal and vertical speed.

Several authors have considered storage location assignment in a block stacking environment. The main issue for block stacking design is the determination of the lane depths in order to minimize storage space and/or handling time. Several models have been presented that allow a single lane depth throughout the warehouse [28, 29]. Goetschalckx and Ratliff [30] present an efficient dynamic programming algorithm for minimizing storage space that allows a limited number of pre-specified lane depths. Their experiments show that it is desirable to have multiple different lane depths but no more than five. For further research the authors mention that some assumptions need to be tested in practice and that extended procedures should be developed that incorporate storage space and handling time considerations. For an extensive literature survey on block stacking we refer to Goetschalckx and Ratliff [30].

Roll and Rosenblatt [31] investigate the space requirements for grouped storage versus randomized storage. It has many advantages to store *related products*, e.g., products from the same shipment or products that are often requested together (correlated products), close to each other. A disadvantage may be the resulting low space utilization. The authors perform a simulation study to estimate the increased space requirements.

3. Control of warehousing operations

The planning policies define a framework under which the control of warehousing operations takes place. Some control problems in warehousing systems are:

- Batching of orders.
- Routing and sequencing.
- Dwell point positioning.

We discuss these issues in Sections 3.1 to 3.3, respectively.

3.1. *Batching of orders*

Batching is a popular strategy for reducing the mean travel time per order. A batch is a set of orders that is picked in a single tour. The orders in the batch may not exceed the storage capacity of the order-picking vehicle. Furthermore, we may maximize the system throughput by establishing large batches with orders at nearby pick locations. However, large batches will give rise to large response times. Moreover, only selecting orders at nearby pick locations might excessively delay orders at the far end of the warehouse. Accordingly, the trade-off between efficiency and urgency must be observed. This trade-off may be achieved by selecting a block with the most urgent orders (*static approach*) and find an order batching within the block that minimizes travel time. All orders in the block are executed before the next block is released. Another approach may be to assign due dates to the orders and release each order immediately (*dynamic approach*). Subsequently, we establish a schedule that satisfies these due dates.

Many batching heuristics have been presented in the literature for minimizing travel time for the static approach. Most heuristics first select a *seed order* for a batch and subsequently expand the batch with orders that have *proximity* to the seed order as long as the vehicle capacity is not exceeded. The distinctive factor is the measure for the proximity of orders/batches.

Armstrong *et al.* [32] consider batching with fixed batch sizes and present an Integer Programming model. Elsayed [33], Elsayed and Stern [34], Gibson and Sharp [35] and Rosenwein [36] consider batching in a parallel aisle warehouse. Elsayed [33] measures proximity by the number of common locations. Elsayed and Stern [34] consider variations of this measure and a new measure being the sum of the distances of each of the locations in the candidate order to the closest location in the seed order. None of the measures seemed to produce consistently superior results. Gibson and Sharp [35] consider a measure similar to the latter measure in Elsayed and Stern [34] and show that it outperforms a space filling curve approach. Rosenwein [36] uses two measures. One being the number of extra aisles that must be visited when an order is added to a batch. The other averages the aisle numbers and batches the orders for which this average is nearest. The former measure outperforms the latter in the experiments.

Elsayed and Unal [37], Gibson and Sharp [35], Hwang *et al.* [38] and Hwang and Lee [39] consider order-picking with man-aboard S/R machines. Elsayed and Unal [37] consider time-saving heuristics. Gibson and Sharp [35] use a space filling curve. Hwang *et al.* [38] partition the rack into clusters of storage locations and measure proximity between orders by the overlap in the clusters. Finally, Hwang and Lee [39] consider for each order a region in the rack that may be traveled without increasing travel time. Proximity is measured by the overlap in these regions. Pan and Liu [40] recommend this heuristic in a comparitive study of batching heuristics presented in the literature for man aboard S/R machine operations.

Few batching procedures have been published that observe due dates. Elsayed *et al.* [41] present a batching heuristic that considers due dates for an order-picking operation with man aboard S/R machines. The objective is to minimize earliness and tardiness penalties. The heuristic first establishes batches and subsequently determines the release times for the batches. Elsayed and Lee [42] consider sequencing and batching of storage and retrieval orders to tours such that the total tardiness of the retrieval orders is minimized.

3.2. *Routing and sequencing*

In this section we discuss routing and sequencing in warehousing systems. In Section 3.2.1 we consider unit-load retrieval systems. Subsequently, in Section 3.2.2 we discuss order-picking systems. Finally, in Section 3.2.3 we observe carousel systems.

3.2.1. *Unit-load retrieval operations*

The sequencing of storage/retrieval requests in an AS/RS has received extensive attention in the literature. Hausman *et al.* [3] only consider single command cycles. Graves *et al.* [2] study the effects of performing dual command cycles. They observe travel time reductions of up to 30%.

Han *et al.* [43] show that the AS/RS throughput performance may be improved by cleverly sequencing the retrieval requests, so that the interleaving travel time between storage and retrieval locations in a dual command cycle is reduced. The observed time savings depend on the number of open locations in the racks and the number of available storage and retrieval requests.

Similar to Section 3.1 we may distinguish the static and dynamic approach.

Han *et al.* [43] suggest the well-known *nearest neighbor* rule for finding a sequence of storage and retrieval requests under the static approach. They also discuss the *no cost zone* for the Chebyshev metric, i.e., the area in the rack that may be visited for a storage without extra (Chebyshev) travel time, while traveling from the input station to a retrieval location. Based on this, they present the *shortest leg* heuristic. However, this heuristic was outperformed by the nearest neighbor heuristic due to the fact that it appeared to fill up the area close to the I/O station.

Lee and Schaefer [44] use a Linear Assignment Problem (LAP) to solve the sequencing problem when there is an equal number of storage and retrieval requests. It may occur that the solution of the Linear Assignment Problem corresponds to an infeasible sequence since a location is to be used for storage while the product will not have been retrieved yet. The authors use the ranking algorithm of Murty [45] which repetitively finds the next best solution of the LAP. Since this might require excessive computation times until a feasible solution is found, they impose a limit on the number of iterations and apply a heuristic that constructs a feasible solution at each iteration. Lee and Schaefer [46] show that under the dedicated storage policy the LAP establishes an optimal solution for the static approach. Extending the static approach to a dynamic situation (resolving the LAP after each alteration of the order set) does not give good results since it was outperformed by a simple greedy heuristic. Furthermore, they show that the dynamic approach establishes average savings of 10–20% of the interleaving time compared to the static approach.

Van den Berg [47] also considers the dedicated storage policy and solves the problem to optimality in polynomial time by modeling it as a Transportation Problem. The model is an extension of Lee and Schaefer [46] since it allows arbitrary positions of the input and output stations and any numbers of storage and retrieval requests.

Lee and Kim [48] consider the problem of minimizing earliness and tardiness penalties when all storage and retrieval requests have a common due date.

Several simulation studies have been presented of an AS/RS for the dynamic approach, including those of Schwarz *et al.* [4], Linn and Wysk [49,50], Seidmann [51] and Linn and Xie [52]. Schwarz *et al.* [4] substantiate the equivalence of the *Closest Open Location* (COL) rule and randomized storage under realistic conditions. Moreover, they compare the mean cycle time of the closest open location rule to that of the class-based storage policy, with two or three classes, while considering interleaving and different queue lengths of retrievals waiting. Finally they consider imperfect information on the turnover rates of products. They find that the class-based storage policy can tolerate fairly large errors in the turnover rate forecasting without increasing the mean cycle time considerably. Linn and Wysk [49] systematically evaluate a number of storage and retrieval selection rules when the product demand shows seasonal trend. Seidmann [51] presents a dynamic control approach that modifies its policies based on the number of requests waiting and changes in turnover rate. Linn and Wysk [50] present an expert system that adapts its controls depending on the utilization rate of the AS/RS. Linn and Xie [52] consider an AS/RS in an assembly environment. To prevent delay in the assembly, urgency rules are used that give priority to storage and retrieval requests that are close to their given due dates.

Keserla and Peters [53] and Sarker *et al.* [54] consider an AS/RS with S/R machines that have dual shuttles. This allows two storages and two retrievals per cycle. Moreover, one storage may be performed immediately after a location has been cleared by a retrieval. For an extensive review of travel time models in AS/RS's we refer to Sarker and Babu [55].

3.2.2. *Order-picking operations*

Ratliff and Rosenthal [56] present a dynamic programming algorithm that solves the *Traveling Salesman Problem* (TSP) in a parallel aisle warehouse with cross-over aisles at both ends of each aisle. The computation time of this algorithm is linear in the number of stops. They claim that the problem remains tractable if there are three crossovers per aisle.

Petersen [57] evaluates the performance of five routing heuristics in comparison with the algorithm of Ratliff and Rosenthal [56]. The best heuristics were on average 10% over optimal for various warehouse shapes, locations of the I/O station and pick list sizes. Even the best of the five solutions was on average 5% over the optimal solution.

Goetschalckx and Ratliff [58] give an efficient algorithm for order-picking in a warehouse with non-negligible aisle width. In wide aisles two way travel is possible, traffic can turn and pass and it is possible to use fork lifts for picking. It appeared that savings of up to 30% are possible by picking both sides of the aisle in the same pass rather than picking one side first and returning to pick the other side. Goetschalckx and Ratliff [59] consider the problem of determining the optimal stop positions of an order-picking vehicle in an aisle when the order-picker is allowed to perform multiple picks per stop. They propose an efficient dynamic programming algorithm for the instance that the travel time of the order-picker is measured with the rectilinear metric.

The problem of sequencing picks for a man-aboard S/R machine operation in one aisle is an instance of the TSP with the Chebyshev or rectilinear metric, depending on the travel characteristics of the crane. Gudehus [1] describes the widely used *band heuristic*. This heuristic divides the rack into two horizontal bands. First the locations on the lower band are visited on increasing x-coordinate, subsequently the locations on the upper band are visited on decreasing x-coordinate. Any even number of bands can be used, however two bands give the best results for up to 25 picks [11].

The *convex hull* of a set of nodes is the smallest convex area that includes all nodes. Golden and Stewart [60] discuss the property that every TSP for which travel times are measured by the *Euclidean metric* has an optimal solution in which the nodes on the boundary of the convex hull are visited in the same sequence as if the boundary of the convex hull itself were traced. The Euclidean metric or L_2-*norm* is defined as: $\sqrt{\Delta x^2 + \Delta y^2}/v$, when Δx and Δy denote the translations in horizontal and vertical direction, respectively, and v denotes the travel speed. Akl and Toussaint [61] present a fast algorithm for finding the convex hull. Allison and Noga [62] prove the property for the *rectilinear metric* and Goetschalckx [63] for the Chebyshev metric. The rectilinear metric or L_1-norm is defined as: $\Delta x/v^x + \Delta y/v^y$, when Δx and Δy denote the translations in horizontal and vertical direction, respectively, and v^x and v^y denote the travel speeds in horizontal and vertical direction, respectively. Note that Chebyshev travel is equivalent to rectilinear travel with the system of axes rotated over 45 degrees. Bozer *et al.* [64] present a heuristic that uses the convex hull of the rack locations as an initial subtour. Subsequently, the locations in the interior of the convex hull are inserted. For the Chebyshev and the rectilinear metric some locations can be inserted without increasing the travel time. Bozer *et al.* [64] also present an improved version of the band heuristic that blocks out a central portion of the rack. The band heuristic is executed for the remaining locations, after which locations in the blocked area are inserted. After constructing the tour, 2-opt and 3-opt local exchange routines are applied which attempt to reduce the tour-length.

Hwang and Song [65] consider the situation where the order-picking truck performs Chebyshev travel below a predetermined height, above this height it adopts rectilinear travel to ensure the safety of the order-picker. They present a heuristic that considers the convex hull for Chebyshev travel and rectilinear hull for rectilinear travel.

Daniels *et al.* [66] consider the situation where products are stored at multiple locations and the pick location for a product may be selected from any of these locations. Such an approach often will not be acceptable for the following two reasons. Firstly, it propagates aging of the inventory, since products are not necessarily retrieved according to a First In First Out (FIFO) policy. However, even for non-deteriorating items this often is not desirable. Secondly, it increases the storage space requirements, since there will be multiple incomplete pallets in the warehouse each occupying a complete storage location. They present six heuristics and a lower bound. Some heuristics perform close to the lower bound on average.

3.2.3. *Carousel operations*

The pick sequencing problem in carousel systems has received considerable attention in the literature. Bartholdi and Platzman [67] consider sequencing of picks in a single order. They assume that the time needed by a (robotic) picker to move between bins within the same carrier (or shelf) is negligible compared to the time to rotate the carousel to the next carrier (or shelf). This assumption reduces the problem to finding the shortest Hamiltonian path on a circle. They present a linear time algorithm that finds an optimum solution. Wen and Chang [68] also consider sequencing picks in a single order. They assume that the time to move between bins within the same carrier or shelf may not be neglected. They present three heuristics for this situation, based upon the algorithm in Bartholdi and Platzman [67].

Several authors have considered the situation where the order-picker consecutively picks multiple orders thereby completing all picks in an order before commencing with the next order, i.e., all picks in an order are performed consecutively. Ghosh and Wells [69] and van den Berg [70] present efficient dynamic programming algorithms that find an optimal pick sequence for picking multiple orders when the sequence of the orders is fixed (the sequence of the picks in the orders is free). Bartholdi and Platzman [67] consider the problem when the order sequence is free, yet picks within the same order must be performed consecutively. They impose the extra constraint that each order is picked along its *shortest spanning interval*, and present a heuristic for the problem with the extra constraint. Van den Berg [70] presents a polynomial time algorithm that solves the problem with the extra constraint to optimality. The author also shows that the solution of the algorithm for the problem with the extra constraint is at most 1.5 revolutions of the carousel above a lower bound for the problem without the extra constraint. He also reveals that the upper bound of one revolution presented by Bartholdi and Platzman [67] for their heuristic is incorrect.

3.2.4. *Relocation of storage*

Jaikumar and Solomon [71] address the problem of relocating pallets with a high expectancy of retrieval in an AS/RS to locations closer to the I/O station during off-peak hours. The authors assume that there is sufficient time, so that travel time considerations are omitted from the model. They present an efficient algorithm that minimizes the number of relocations in order to meet the expected throughput. Muralidharan *et al.* [72] combine the benefits of randomized storage (less storage space) and class-based storage (less travel time). They suggest randomized location assignment when storing pallets and relocation of pallets with respect to their turnover rates during idle periods.

3.3. *Dwell point positioning*

The dwell point in an AS/RS is the position where the S/R machine resides when the system is idle. The dwell point is selected such that the expected travel time to the position of the first transaction after the idle period is minimized. An effective dwell point strategy may reduce the response times of the AS/RS, since the S/R machine typically performs a sequence of operations following an idle period. Hence, if the first operation is advanced, then all operations within the sequence are completed earlier.

The selection of the dwell point has received considerable attention in the literature. Graves *et al.* [2] select the dwell point at the input/output (I/O) station. Park [73] shows the optimality of this strategy, if the probability of the first operation after an idle period being a storage is at least 0.5. Egbelu [74] presents LP-models for finding the dwell point that minimizes the expected travel time and for finding the dwell point that minimizes the maximum travel time to the first transaction. Egbelu and Wu [75] use simulation to evaluate the performance of several dwell point strategies. Hwang and Lim [76] develop a method that solves finds the optimal dwell point as a Facility Location Problem with rectilinear distances. The computational complexity of that method is equivalent to sorting a set of numbers.

All models that are mentioned so far consider a discrete set of storage locations. Peters *et al.* [77] present an analytic model for finding the optimal dwell point, based on the expressions found by Bozer and White [78].

4. Conclusions

Planning and control of warehousing systems are complex issues. In this paper we have defined a hierarchy of warehousing decisions, that will provide high quality solutions for these complex problems. According to this hierarchy we have discussed the results that have been published in the literature.

The survey shows that many methods and procedures have been developed that significantly outperform the methods that are used in practice. Even modern information technology such as specialized warehouse management systems still use simple heuristics. In many cases, the warehouse performance would be improved by at least 10 intelligent planning and control procedures.

After completing the survey, we would like to make two summarizing remarks.

Firstly, few papers have been published that present algorithms which provide optimal solutions. Beside their optimal performance, these exact algorithms give us insight into the problems and they may be used as benchmarks for heuristic procedures. As the survey shows, most papers discuss heuristic procedures. The use of heuristics is motivated by the fact that most warehousing problems are NP-hard in general. The contribution of such studies may be valuable if the heuristic provides a worst-case bound or if an interesting new model formulation has been presented. However, the performance of many dedicated heuristics will be equaled by general-purpose optimization procedures such as *simulated annealing*, cf. Aarts and Korst [79], and Tabu search, cf. Glover [80]. Consequently, we would like to stress that more effort should be given to the development of new models. Designing new models will establish larger savings than optimizing the existing ones. Clearly, introducing new working procedures will achieve larger savings than optimizing the existing working procedures. For instance, for the forward/reserve problem we have seen that significant time savings are possible by allowing order-picking from the reserve area. These savings considerably exceeded the savings between different allocation rules (cf. Section 2.1).

Secondly, many publications in the survey discuss methods and models that attempt to minimize travel time thereby maximizing throughput. However, in most practical situations maximizing throughput is not the only objective. Orders often have to meet deadlines so that trade-offs must be made between productivity and urgency.

To this end, we conclude with the following suggestion for future research. Flexibilization of labor is an important issue in warehouses. Flexibilization implies that throughout the day personnel are shifted between activities whenever extra capacity is needed. Furthermore, if the available labor capacity is insufficient, then temporary staff are hired from an agency. Accordingly, labor costs will be minimized. Such an approach requires effective capacity planning procedures for the various activities in the warehouse (receiving, storage, order-picking, replenishment, shipping, et cetera). Capacity planning determines the number of personnel and resources that are required at any activity. Furthermore, procedures are needed for scheduling such complicated warehousing operations under tight time constraints. By monitoring progress, resources may be redistributed among activities.

References

[1] Gudehus, T. (1973) *Principles of Order Picking: Operations in Distribution and Warehousing Systems*, W. Girardet, Essen, Germany, (in German).

[2] Graves, S.C., Hausman, W.H. and Schwarz, L.B. (1977) Storage-retrieval interleaving in automatic warehousing systems. *Management Science*. **23**(9), 935–945.

[3] Hausman, W.H., Schwarz, L.B. and Graves, S.C. (1976) Optimal storage assignment in automatic warehousing systems. *Management Science*, **22**(6), 629–638.

[4] Schwarz, L.B., Graves, S.C. and Hausman, W.H. (1978) Scheduling policies for automatic warehousing systems: simulation results. *AIIE Transactions*, **10**(3), 260–270.

[5] Anthony, R.N. (1965) *Planning and control systems: a framework for analysis*. Harvard University Graduate School of Business Administration, Boston, MA.

[6] Ashayeri, J. and Gelders, L.F. (1985) Warehouse design optimization. *European Journal of Operational Research*, **21**, 285–294.

[7] Hariga, M.A. and Jackson, P.L. (1996) The warehouse scheduling problem: formulation and algorithms. *IIE Transactions*, **28**(2), 115–127.

[8] van Oudheusden, D.L., Tzen, Y.-J.J. and Ko, H.-T. (1988) Improving storage and order picking in a person-on-board AS/R system. *Engineering Costs and Production Economics*, **13**, 273–283.

[9] Frazelle, E.H., Hackman, S.T., Passy, U. and Platzman, L.K. (1994) The forward-reserve problem, in *Optimization in Industry 2*, Ciriani, T.A. and Leachman, R.C. (eds), John Wiley, pp. 43–61.

[10] Brynzér, H. and Johansson, M.I. (1995) Design and performance of kitting and order picking systems. *International Journal of Production Economics*, **41**, 115–125.

[11] Bozer, Y.A. (1985) *Optimizing throughput performance in designing order picking systems*. PhD thesis, Georgia Institute of Technology, Atlanta, GA.

[12] Hackman, S.T. and Rosenblatt, M.J. (1990) Allocating items to an automated storage and retrieval system. *IIE Transactions*, **22**(1), 7–14.

[13] van den Berg, J.P., Sharp, G.P., Gademann, A.J.R.M. and Pochet, Y. (1998) Forward-reserve allocation in a warehouse with unit-load replenishments. *European Journal of Operational Research*, **111**, 98–113.

[14] Frazelle, E.A. and Sharp, G.P. (1989) Correlated assignment strategy can improve order-picking operation. *Industrial Engineering*, **4**, 33–37.

[15] Lee, M.-K. (1992) A storage assignment policy in a man-on-board automated storage/retrieval system. *International Journal of Production Research*, **30**(10), 2281–2292.

[16] Rosenwein, M.B. (1994) An application of cluster analysis to the problem of locating items within a warehouse. *IIE Transactions*, **26**(1), 101–103.

[17] van Oudheusden, D.L. and Zhu, W. (1992) Storage layout of AS/RS racks based on recurrent orders. *European Journal of Operational Research*, **58**(1), 48–56.

[18] Hardy, J.A., Littlewood, A.B. and Polya, A. (1949) *Inequalities*, Prentice-Hall, Englewood Cliffs, NJ.

[19] Goetschalckx, M. and Ratliff, H.D. (1990) Shared storage policies based on the duration stay of unit loads. *Management Science*, **36**(9), 1120–1132.

[20] Guenov, M. and Raeside, R. (1989) Real time optimization of man on board order-picking, in *Proceedings of the 10th International Conference on Automation in Warehousing*, pp. 89–94.

[21] Hwang, H. and Lee, S.B. (1990) Travel-time models considering the operating characteristics of the storage and retrieval machine. *International Journal of Production Research*, **28**(10), 1779–1789.

[22] Chang, D.-T., Wen, U.-P. and Lin, J.T. (1995) The impact of acceleration/deceleration on travel-time models for automated storage/retrieval systems. *IIE Transactions*, **27**(1), 108–111.

[23] Rosenblatt, M.J. and Eynan, A. (1989) Deriving the optimal boundaries for class-based automatic storage/retrieval systems. *Management Science*, **35**(12), 1519–1524.

[24] Eynan, A. and Rosenblatt, M.J. (1994) Establishing zones in single-command class-based rectangular AS/RS. *IIE Transactions*, **26**(1), 38–46.

[24] van den Berg, J.P. (1996) Class-based storage allocation in a single command warehouse with space requirement constraints. *International Journal of Industrial Engineering*, **3**(1), 21–28.

[26] Jarvis, J.M. and McDowell, E.D. (1991) Optimal product layout in an order picking warehouse. *IIE Transactions*, **23**(1), 93–102.

[27] Guenov, M. and Raeside, R. (1992) Zone shapes in class based storage and multicommand order picking when storage/retrieval machines are used. *European Journal of Operational Research*, **58**(1), 37–47.

[28] Berry, J.R. (1968) Elements of warehouse layout. *International Journal of Production Research*. **7**(2), 105–121.

[29] Marsh, W.H. (1979) Elements of block storage design. *International Journal of Production Research*, **17**(4), 377–394.

[30] Goetschalckx, M. and Ratliff, H.D. (1991) Optimal lane depths for single and multiple products in block stacking storage systems. *IIE Transactions*, **23**(3), 245–258.

[31] Roll, Y. and Rosenblatt, M.J. (1983) Random versus grouped storage policies and their effect on warehouse capacity. *Material Flow*, **1**, 199–205.

[32] Armstrong, R.D., Cook, W.D. and Saipe, A.L. (1979) Optimal batching in a semi-automated order picking system. *Journal of the Operational Research Society*, **30**(8), 711–720.

[33] Elsayed, E.A. (1981) Algorithms for optimal material handling in automatic warehousing systems. *International Journal of Production Research*, **19**(5), 525–535.

[34] Elsayed, E.A. and Stern, R.G. (1983) Computerized algorithms for order processing in automated warehousing systems. *International Journal of Production Research*, **21**(4), 579–586.

[35] Gibson, D.R. and Sharp, G.P. (1992) Order batching procedures. *European Journal of Operational Research*, **58**(1), 57–67.

[36] Rosenwein, M.B. (1996) A comparison of heuristics for the problem of batching orders for warehouse selection. *International Journal of Production Research*, **34**(3), 657–664.

[37] Elsayed, E.A. and Unal, O.I. (1989) Order batching algorithms and travel-time estimation for automated storage/retrieval systems. *International Journal of Production Research*, **27**(7), 1097–1114.

[38] Hwang, H., Baek, W. and Lee, M.-K. (1988) Clustering algorithms for order picking in an automated storage and retrieval system. *International Journal of Production Research*, **26**(2), 189–201.

[39] Hwang, H. and Lee, M.-K. (1988) Order batching algorithms for a man-on-board automated storage and retrieval system. *Engineering Costs and Production Economics*, **13**, 285–294.

[40] Pan, C.-H. and Liu, S.-Y. (1995) A comparative study of order batching algorithms. *Omega*, **23**(6), 691–700.

[41] Elsayed, E.A., Lee, M.-K., Kim, S. and Scherer, E. (1993) Sequencing and batching procedures for minimizing earliness and tardiness penalty of order retrievals. *International Journal of Production Research*, **31**(3), 727–738.

[42] Elsayed, E.A. and Lee, M.-K. (1996) Order processing in automated storage/retrieval systems with due dates. *IIE Transactions*, **28**(7), 567–577.

[43] Han, M.-H., McGinnis, L.F., Shieh, J.S. and White, J.A. (1987) On sequencing retrievals in an automated storage/retrieval system. *IIE Transactions*, **19**(1), 56–66.

[44] Lee, H.F. and Schaefer, S.K. (1996) Retrieval sequencing for unit-load automated storage and retrieval systems with multiple openings. *International Journal of Production Research*, **34**(10), 2943–2962.

[45] Murty, K.G. (1968) An algorithm for ranking all the assignments in order of increasing costs. *Operations Research*, **16**(3), 682–687.

[46] Lee, H.F. and Schaefer, S.K. (1997) Sequencing methods for automated storage and retrieval systems with dedicated storage. *Computers and Industrial Engineering*, **32**(2), 351–362.

[47] van den Berg, J.P. (1996) *Planning and control of warehousing systems*. PhD thesis, University of Twente, Faculty of Mechnical Engineering, Enschede, The Netherlands.

[48] Lee, M.-K. and Kim, S.-Y. (1995) Scheduling of storage/retrieval orders under a just-in-time environment. *International Journal of Production Research*, **33**(12), 3331–3348.

[49] Linn, R.J. and Wysk, R.A. (1987) An analysis of control strategies for an automated storage/retrieval system. *INFOR*, **25**(1), 66–83.

[50] Linn, R.J. and Wysk, R.A. (1990) An expert system framework for automated storage and retrieval system control. *Computers & Industrial Engineering*, **18**(1), 37–48.

[51] Seidmann, A. (1988) Intelligent control schemes for automated storage and retrieval systems. *International Journal of Production Research*, **26**(5), 931–952.

[52] Linn, R.J. and Xie, X. (1993) A simulation analysis of sequencing rules in a pull-based assembly facility. *International Journal of Production Research*, **31**(10), 2355–2367.

[53] Keserla, A. and Peters, B.A. (1994) Analysis of dual-shuttle automated storage/retrieval systems. *Journal of Manufacturing Systems*, **13**(6), 424–434.

[54] Sarker, B.R., Mann, Jr., L. and Leal Dos Santos, J.R.G. (1994) Evaluation of a class-based storage scheduling technique applied to dual-shuttle automated storage and retrieval systems. *Production Planning & Control*, **5**(5), 442–449.

[55] Sarker, B.R. and Babu, P.S. (1995) Travel time models in automated storage/retrieval systems: a critical review. *International Journal of Production Economics*, **40**, 173–184.

[56] Ratliff, H.D. and Rosenthal, A.S. (1983) Order-picking in a rectangular warehouse: a solvable case of the traveling salesman problem. *Operations Research*, **31**(3), 507–521.

[57] Petersen, II, C.G. (1997) An evaluation of order picking routeing policies. *International Journal of Operations & Production Management*, **17**(11), 1098–1111.

[58] Goetschalckx, M. and Ratliff, H.D. (1988) Order picking in an aisle. *IIE Transactions*, **20**(1), 53–62.

[59] Goetschalckx, M. and Ratliff, H.D. (1988) An efficient algorithm to cluster order picking items in a wide aisle. *Engineering Costs and Production Economics*, **13**(1), 263–271.

[60] Golden, B.L. and Stewart, W.R. (1985) Empirical analysis of heuristics, in *The Traveling Salesman Problem*, Lawler, E.L., Lenstra, J.K., Rinnooy Kan, A.H.G. and Shmoys, D.B. (eds), John Wiley &Sons, Chichester, UK, Ch. 7.

[61] Akl, S.G. and Toussaint, G.T. (1978) A fast convex hull algorithm. *Information Processing Letters*, **7**, 219–223.

[62] Allison, D.C.S. and Noga, M.T. (1984) The rectilinear traveling salesman problem. *Information Processing Letters*, **18**(4), 195–199.

[63] Goetschalckx, M.P. (1983) *Storage and retrieval policies for efficient order picking*. PhD thesis, Georgia Institute of Technology, Atlanta, GA.

[64] Bozer, Y.A., Schorn, E.C. and Sharp, G.P. (1990) Geometric approaches to solve the Chebyshev traveling salesman problem. *IIE Transactions*, **22**(3), 238–254.

[65] Hwang, H. and Song, J.Y. (1993) Sequencing picking operations and travel time models for man-on-board storage retrieval system. *International Journal of Production Economics*, **29**, 75–88.

[66] Daniels, R.L., Rummel, J.L. and Schantz, R. (1998) A model for warehouse order picking. *European Journal of Operational Research*, **105**, 1–17.

[67] Bartholdi, III, J.J. and Platzman, L.K. (1986) Retrieval strategies for a carousel conveyor. *IIE Transactions*, **18**(2), 166–173.

[68] Wen, U.-P. and Chang, D.T. (1988) Picking rules for a carousel conveyor in an automated warehouse. *Omega*, **16**(2), 145–151.

[69] Ghosh, J.B. and Wells, C.E. (1992) Optimal retrieval strategies for carousel conveyors. *Mathematical Computer Modelling*, **16**(10), 59–70.

[70] van den Berg, J.P. (1996) Multiple order pick sequencing in a carousel system: a solvable case of the rural postman problem. *Journal of the Operational Research Society*, **47**(12), 1504–1515.

[71] Jaikumar, R. and Solomon, M.M. (1990) Dynamic operational policies in an automated warehouse. *IIE Transactions*, **22**(4), 370–376.

[72] Muralidharan, B., Linn, R.J. and Pandit, R. (1995) Shuffling heuristics for the storage location assignment in an AS/RS. *International Journal of Production Research*, **33**(6), 1661–1672.

[73] Park, B.C. (1992) *Analytical models and optimization strategies for automated storage/retrieval system operations*. PhD thesis, Georgia Institute of Technology, Atlanta, GA.

[74] Egbelu, P.J. (1991) Framework for dynamic positioning of storage/retrieval machines in an automated storage/retrieval system. *International Journal of Production Research*, **29**(1), 17–37.

[75] Egbelu, P.J. and Wu, C.-T. (1993) A comparison of dwell point rules in an automated storage/retrieval system. *International Journal of Production Research*, **31**(11), 2515–2530.

[76] Hwang, H. and Lim, J.M. (1993) Deriving an optimal dwell point of the storage/retrieval machine in an automated storage/retrieval system. *International Journal of Production Research*, **31**(11), 2591–2602.

[77] Peters, B.A., Smith, J.S. and Hale, T.S. (1996) Closed form models for determining the optimal dwell point location in automated storage and retrieval systems. *International Journal of Production Research*, **34**(6), 1757–1771.

[78] Bozer, Y.A. and White, J.A. (1984) Travel-time models for automated storage/retrieval systems. *IIE Transactions*, **16**(4), 329–338.

[79] Aarts, E. and Korst, J. (1989) *Simulated Annealing and Boltzmann Machines: A Stochastic Approach to Combinatorial Optimization and Neural Computing*, Wiley, Chichester, UK.

[80] Glover, F. (1990) Tabu search: a tutorial. *Interfaces*, **20**(4), 74–94.

Biography

Jeroen van den Berg works as a management consultant for Berenschot in The Netherlands. His workfield includes logistic management and information technology (warehouse management systems, advanced planning & scheduling systems, *et cetera*). In 1996 he received his Ph.D. at the Faculty of Mechanical Engineering of the University of Twente in The Netherlands. The title of his thesis was: *Planning and control of warehousing systems*. He received his Masters in Applied Mathematics at the University of Twente in 1992.

Contributed by the Location, Transportation and Distribution Decisions Department.