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Concurrent manual-order-picking warehouse design: a simulation-based design of experiments approach

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The design of manual-order-picking warehouses is a combination of interdependent decisions with enormous possible varieties in design components. The strong interrelationship between these components, in addition to the dynamic and interconnected stochastic nature of the problem; necessitate the utilisation of a simultaneous simulation-based approach. This study proposes a concurrent simulation-based design of experiments approach for the design of manual-order-picking warehouses. The proposed approach can investigate all possible warehousing design combinations with their stochastic nature and interactions; hence, widening the search for performance improvement. The examined design components include warehouse throughput, size, layout, operational policies and manpower/carts. Furthermore, the presented approach captures the probabilistic nature of all the key warehouse functions of receiving, unloading, put away, storage, preparation and picking and shipping; and evaluates the performance of the studied designs using the cycle time for a stock keeping unit in the warehouse. Statistical analysis of the simulation results showed several interesting findings; horizontal layout was preferable over all other types of layouts and small size warehouses perform better than other large sizes. The study has also recommended using high throughput for traditional layout-small size warehouses.

Keywords: warehousing; manual-order-picking; simulation; design of experiments; performance analysis

1. Introduction

Manual-order-picking warehouse is a very common warehouses class; according to De Koster, Le-Duc, and Roodbergen (2007), 80% of warehouses in Western Europe are manually operated. In such systems, manpower plays essential role in conducting the warehouse key functions of receiving, unloading, putting away, storing, order preparation and picking and shipping. Particularly, the order-picking function, in which operators retrieve stock keeping units (SKUs) from storage locations in single or multiple stop tour; is the most labour intensive, accordingly expensive, function (Petersen 2002; Roodbergen and Vis 2006). In fact, most of the warehouses' operational cost is contributed to order-picking (Tompkins et al. 2010).

Warehouse design is an interdependent cluster of decisions at the strategic, tactical and operational levels; aiming to meet particular performance criteria (Rouwenhorst et al. 2000). Gu, Goetschalckx, and McGinnis (2010) classified these decisions into five categories; the warehouse overall structure, sizing and dimensioning, layout design, equipment selection and selection of operational policies. Traditionally, warehouse design is implemented in a sequential manner. For example, after deciding on throughput and size, suitable layout is selected, racking and material handling systems are then chosen, and finally operational polices are adopted. As each design component is predetermined before choosing its successor; this approach limits the interactions between the design components to a small set of components levels. Consequently, only a limited spectrum of design component levels can be investigated, with limited chance of improving performance.

Manual-order-picking warehouse design, including the operational policies, has been a research topic over the past few decades. The problem is mainly approached using analytical, simulation and mixed analytical-simulation methods (Cormier and Gunn 1996; Gu, Goetschalckx, and McGinnis 2010). Although analytical models are usually design oriented (Gu, Goetschalckx, and McGinnis 2010), and have proved successes in different cases (Roodbergen and Koster 2001; Fukunari and Malmborg 2008; Bukchin, Khmelnitsky, and Yakuel 2012; Chen et al. 2013; Li, Huang, and Dai 2017; Rao and Adil 2017); such methods can only consider specific warehouse design combinations (Roodbergen, Vis, and Taylor 2015). Simulation on the other hand, can simultaneously consider all possible warehousing design combinations. In their proposed framework for warehouse design, Baker and Canessa (2009) suggested adopting simulation in

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several steps of the framework, including establishing the unit load, selection of equipment, calculating capacity and performance evaluation. Much research has demonstrated the applicability of simulation in several warehousing design elements including layout design (Caron, Marchet, and Perego 2000; Dukic, Vedran, and Opetuk 2010), size (Petersen 2002), manpower and equipment (Kosfeld 1998) and operational policies (Macro and Salmi 2002; Petersen and Aase 2004; Altarazi and Ammouri 2010; Chackelson et al. 2013; Emami, Arabzad, and Sajjadi 2014; Shqair, Altarazi, and Al-Shihabi 2014). The next section presents more details about simulation-based research for warehouse design.

The enormous aspects of the warehouse design problem including decisions in different planning levels for the five design categories, as detailed in Section 3; and the strong interrelationship between the design components require the analysis to be conducted in a concurrent manner. Furthermore, the dynamic and interconnected stochastic nature of the problem necessitates the utilisation of simulation modelling. This study proposes a concurrent simulation-based design of experiments (DoE) approach for designing manual-order-picking warehouse. Considering their full combinations at multi levels, the proposed approach considers five key manual warehouse design components; throughput, size, layout, operational policies and number of utilised manpower/carts. Furthermore, the presented approach integrates all the key warehouse functions (i.e. receiving, unloading, put away, storage, preparation and picking, shipping). The performance of studied designs is evaluated using a supply chain-oriented criterion; the average cycle time for an SKU within a warehouse, that is, the average elapsed time between entering and shipping an SKU to/from a warehouse. This cycle time is different from the order-to-delivery time which is usually used in literature for order-picking performance measurement. The adopted cycle time considers the time of all the functions in a warehouse, not just the picking, preparation and loading times; hence, it is an appropriate evaluator for warehouses performance from the entire supply chain perspective.

2. Related research

An overview of previous simulation-based research related to warehouse design is presented in this section. Since warehouses are typically stochastic discrete-event systems, most simulation-related research have adopted discrete-event simulation (DES) type. Other simulation modelling types, such as agent-based modelling (ABM) and Petri nets (PN) formal modelling were also implemented. This section also briefly overviews literature regarding adopted simulation for automated storage/retrieval systems (AS/RS) used in warehouses.

Caron, Marchet, and Perego (2000) presented a DES approach for efficient manual-order-picking warehouse layout design using random or cube per order index storage policies. They found that the optimal number of aisles depends on both strategic and operational decisions such as the size of the picking area in a warehouse, batch size, number of picks in a tour, and utilised storage policy. In a comparable DES-based study, for both random and volume-based storage policies, Petersen (2002) studied the effect of the warehouse configuration, represented by the number of aisles per zone and the length of aisles, on the total travelled time. The results showed that the warehouse shape is significantly affected by the storage policy, aisle length and number of aisles, absence of a back cross-aisle and number of SKUs on the picking list. Dukic, Vedran, and Opetuk (2010) used DES to differentiate between different warehouse layouts; mainly traditional with/without aisles and fishbone. They found that the fishbone layout is very suitable for pallet picking, yet, traditional layouts were found preferable in the case of multiple picking routes. Emami, Arabzad, and Sajjadi (2014) developed a DES model for to optimise the trucks' loading and unloading time in warehouses. The processes covered by the model mainly include SKU' checking, unloading, storing, delivering and loading.

Among all manual-order-picking warehouse design components, the 'selection of operational policies' has attracted most simulation, particularly DES, studies. Petersen (2000) simulated five different order-picking policies: strict order, batch, sequential zone, concurrent zone and wave picking. Petersen and Aase (2004) introduced a simulation model to examine the effect of several picking, routing, and storage policies on the total distance travelled within the warehouse to fulfil orders. Sensitivity analyses for the effect of order size, warehouse shape and demand distribution were also performed. They found that orders batching and class-based or volume-based storage policies would provide the minimum travelled distance. Macro and Salmi (2002) developed a universal warehouse storage simulation model to analyse the storage capacity and rack efficiency of medium volume small-SKUs and medium volume large-SKUs warehouses. Their results provided the type, amount and layout of pallet storage required for the two warehouses scenarios. Altarazi and Ammouri (2010) presented a DES-based tool for selecting key warehouse resources considering both generic and case-based warehouse characteristics. Their results showed that adopting the volume-based storage policy and changing the manner of using the gating system can significantly affect warehouse resources utilisation. Conceptually similar to the work of Altarazi and Ammouri (2010) but with focusing on detailed operational policy, Chackelson et al. (2013) presented a DoE-DES approach for simultaneously configuring and evaluating different warehouse policies levels. Altarazi, Ammouri, and Alzubi (2012) proposed a DES methodology for manual-order-picking warehouse design considering key design elements in various combinations and evaluated the performance of such combinations using multi performance criteria. The suggested methodology provided an answer of what design characteristics should be adopted in order to optimise a particular performance criterion. Roodbergen, Vis, and Taylor (2015) presented a warehouse design DES-based method while concurrently considering scenarios of layout and operational policies. The results revealed that the concurrent approach has a large potential in improving the warehouse performance.

Few tries can be found in literature regarding implementing ABM and PN modelling for the warehouse design problem. Ito and Abadi (2002) proposed an ABM for simulating a warehouse. The model integrated three subsystems; agent-based communication system, agent-based material handling system and agent-based inventory planning and control system. The model was validated by comparing its simulation results with a prototype system performance. Kim et al. (2002) presented an ABM for the operations' control of an actual industrial warehouse. In the model, the agents can communicate with each other in a dynamic real-time fashion and can make decisions, such as scheduling decisions, accordingly. Shqair, Altarazi, and Al-Shihabi (2014) adopted ABM to simultaneously simulate the relations of strategic (number of aisles, aisle length and number of storage blocks), tactical (storage assignment policy) and operational decisions (routing policy and order size) pertaining to warehouse design. The study showed that having one cross-aisle only and using a class-based storage policy can significantly decrease the distance travelled. This study also concluded that the best routing policy is layout-dependent decision. Elbert et al. (2016) have also adopted ABM to evaluate the efficiency of manual-order-picking routing policies when pickers deviate from pre-specified routes. They concluded that even with these human-based deviations, optimal routing would remain the preferred strategy to implement. Basile, Pasquale, and Domenico (2012) used PN formal modelling approach for online monitoring, scheduling and rescheduling of warehouses' operational activities. Buil and Piera (2008) used Coloured PN (CPN) to integrate warehouse functions (receiving, storage, picking and shipping) at the strategic, tactical and operational levels. The proposed approach resulted in considerable savings on equipment and workers costs.

In addition to adopting simulation modelling for manual-order-picking warehouse, simulation has been widely used also for the design and utilisation of various AS/RS types (Roodbergen and Vis 2009). Lee (1992) analysed class-based storage for a man-on-board AS/RS through simulation. Rosenblatt, Roll, and Zyser (1993) suggested a simulation-analytical approach to determine the size of an AS/RS system. Randhawa and Shroff (1995) extended this study, using simulation, to investigate different inputs/outputs configurations on AS/RS multi-criteria performance including throughput, mean waiting time and maximum waiting time. Potrč et al. (2004) implemented DES to determine travel times and throughput for AS/RS considering different high storage racks and velocity profiles. Ekren et al. (2010) presented a DES-DoE approach for unit load AS/RS to identify the factors affecting the system's performance. Lerher, Šraml, and Potrč (2011) presented DES and analytical modelling for evaluating the performance of mini-load multi-shuttle ASRS. Dukic, Opetuk, and Lerher (2015) used simulation to test a throughput model for single dual-tray vertical lift module (VLM) AS/RS with a human order-picker. Recently, Rosi et al. (2016) also presented a DES model for evaluating the VLM performance while considering different configuration designs and velocity profiles.

The above review of literature indicates:

- The suitability and capability of simulation modelling in designing manual-order-picking warehouses and automated warehouses.
- The lack of comprehensive concurrent simulation approach for designing manual-order-picking warehouses. Most research on warehouse design via simulation considered single design component, mainly operational policies (Rosenblatt, Roll, and Zyser 1993; Petersen and Aase 2004) and layout and/or sizing (Caron, Marchet, and Perego 2000; Dukic, Vedran, and Opetuk 2010); with less focus on manpower and equipment (Kosfeld 1998; Macro and Salmi 2002) and throughput components. Few researches simultaneously considered two design components; mainly the layout and operational policies (Altarazi and Ammouri 2010; Shqair, Altarazi, and Al-Shihabi 2014; Roodbergen, Vis, and Taylor 2015; Petersen and Aase 2016). Thus, it is the synthesis of all design components that appears to be lacking. As indicated by Gu, Goetschalckx, and McGinnis (2010), it is clear that warehouse design-related research has focused on analysis rather than synthesis.
- Most related simulation-based research focused on the order-picking function (Caron, Marchet, and Perego 2000; Petersen 2002; Petersen and Aase 2004; Chackelson et al. 2013; Shqair, Altarazi, and Al-Shihabi 2014) without integrating other functions such as receiving, put away, unloading, storage, shipping functions. Accordingly, only partial stochastic warehouse's operational data are utilised in these models.
- By focusing on the order-picking function, most related research used the picking-route distance travelled, or its associated time, as an evaluation metric. This metric has two drawbacks; first, it partially evaluates the outbound part (order preparation, picking and loading) and ignores the inbound part (receiving, put away, storage, etc.) of a warehouse functions. Second, the metric is an internal performance indicator which does not consider the supply

chain perspective. Supply chain performance cares about the overall cycle time of a warehouse not its' internal travelling time.

The current research presents an effort to overcome the above-mentioned issues. To this end, the proposed approach models the main components of warehouse design concurrently, considers the full probabilistic nature of warehouse operations, models the key warehouses' functions and adopts a supply chain-oriented performance metric.

3. Warehouse design

This section briefly explains the five key warehouse design decisions considered in this study; throughput, size, layout, operational policies and utilised number of manpower/carts.

Warehouse throughput, which is also called warehouse SKUs flow, represents the flow of SKUs in a warehouse. It is associated with the probabilistic nature of SKUs inflowing and departing the warehouse. Throughput volume is proportionally related to the storage requirement for a warehouse (Cormier and Gunn 1996), accordingly, related to the overall structure of a warehouse (Gu, Goetschalckx, and McGinnis 2010). In fact, different throughputs do not only affect the internal performance of a warehouse but also affect the performance of the rest of the supply chain (Rushton, Croucher, and Baker 2014). In the majority of throughput-considered literature, such as (Petersen and Aase 2004), throughput is represented by the order size with deterministic values. In reality, throughput has a probabilistic nature. In addition, throughput is not only related to the outbound side of the warehouse, which is the ordering side, but it is also related to the inbound side, or the receiving side.

The sizing decision is mainly associated with the required capacity of a warehouse which, in its turn, is related to potential sales. For a particular company or supply chain this decision must also be aligned with its total number of warehouses. The importance of this decision comes from its inverse relation with the warehouse construction and inventory costs (Cormier and Gunn 1996) and its correlation to the targeted customer service level; accordingly, with the overall supply chain performance.

The warehouse layout design issue addresses the decision of locating the various warehouse departments (receiving, sorting, storing, shipping, etc.) and more importantly, the decision of the internal layout design. The internal layout design, also called the aisle configuration problem, mainly covers the determination of the number of blocks in a warehouse (existence of cross-aisle/s or not); the number of aisles, orientation, length and width in each block; and the number and location of pick-up/drop-off (P/D) points (De Koster, Le-Duc, and Roodbergen 2007).

The operational policies in a warehouse can mainly be classified into storage assignment, routing and order-picking or batching (Caron, Marchet, and Perego 1998; Petersen and Aase 2004; Roodbergen and Vis 2006). Storage assignment is related to where SKUs are stored in the warehouse, routing is represented by the path followed by the pickers to retrieve SKUs, and order-picking is associated with the grouping/ungrouping of customer orders in a picking list. Three main storage assignment policies can be found in practice: random, volume-based and class-based. The warehouse routing policy is a variant of the classical travelling Salesman problem (TSP). Generally all TSP algorithms, whether optimal or heuristic, can be adopted as routing policies after some customisation. Traversal routing is one example of heuristic routing policy in which pickers must fully traverse the entire aisle once they enter it. Picking policies include strict-order, batch, zone and wave picking policies.

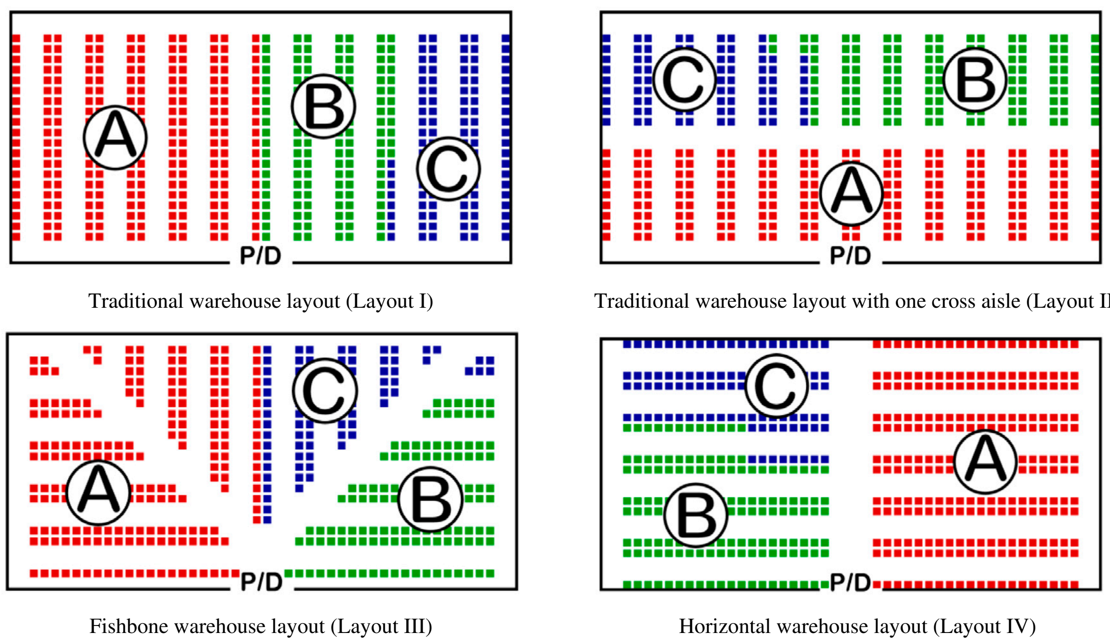
Finally, the equipment selection decision determines the processes and systems to transfer and store products within the warehouse. If properly carried out, this strategic decision can significantly increase profitability. Few researchers addressed the equipment selection problem (Gu, Goetschalckx, and McGinnis 2010).Methods adopted in the equipment selection include optimisation models (Telek 2013), expert systems (Kulak 2005), multi-criteria decision-making (Tuzkaya et al. 2010) and systematic frameworks (Hassan 2010). Mainly these systems evaluate the equipment selection based on their total cost, fixed and variable and technical performance criteria at a given throughput. Since the current research is studying manual warehouses, the equipment selection decision is expressed in terms of the number of manpower/carts utilised in a warehouse.

4. The DoE-simulation framework

This section explains the details of the proposed approach experimental design, simulation modelling and performance evaluation. A description for the adopted warehouse to implement the proposed approach is presented first.

4.1 *Warehouse description and assumptions*

The proposed approach is built based on the operations of a single-floor rectangular warehouse facility. The rectangular shape is selected since it is the optimal geometric shape to store pallets (Berry 1968). As shown by Figure 1, four different warehouse storage layout alternatives are investigated; the traditional one-block layout, with one cross-aisle layout (two-block layout), the horizontal layout and the fishbone layout. The first three layouts are selected since they are common in literature (Roodbergen, Vis, and Taylor 2015; Gue and Meller 2009) while the fishbone layout is selected to represent non-traditional warehouses, that is, warehouses without parallel picking aisles (Gue and Meller 2009; Cardona et al. 2015). For all layouts, the length/width ratio is set approximately as 0.5 since it is approximately the optimal ratio (Bassan, Roll, and Rosenblatt 1980; Pohl, Meller, and Gue 2009). As mentioned earlier, the selection of optimal number of cross-aisles in a warehouse depends on different characteristics (Caron, Marchet, and Perego 2000; Petersen 2002); for comparison purposes, traditional warehouse with one cross-aisle is considered. Table 1 summarises the probabilistic nature for the key warehouse functions; receiving, unloading, put away, storing, order preparation and picking, loading and shipping. This data were identified in consistence with authors' observations; particularly with three manual-order-picking warehouses working in the Jordanian market: a warehouse for hygienic products, a warehouse for food



Traditional warehouse layout (Layout I)

Traditional warehouse layout with one cross aisle (Layout II)

Fishbone warehouse layout (Layout III)

Horizontal warehouse layout (Layout IV)

Figure 1. Warehouse layout alternatives (levels).

Table 1. Warehouse's functions probabilistic data.

Function	Statistical distribution
Receiving (time between arrivals)	Exp(x_1*) h, per N(x_2*,10) SKU
Unloading	N(5, 1) min, per storage compartment
Putting away	N(0.05, 0.01) min per storage compartment per metre
Storing	Delay
Picking	N(0.05, 0.01) min per storage compartment per metre
Preparation	N(30, 5) min per order
Loading	N(5, 1) min per compartment
Shipping (time between departures)	Exp(x_3*) h per x_4* orders. Order contains N(25, 1) for SKU A, N(15, 1) for SKU B, and N(10, 1) for SKU C

*x_1, x_2, x_3, and x_4 vary according to the level of the throughput design component (details in Section 4). For example, for the highest throughput level (as seen in Table 2); $x_1 = 1$, $x_2 = 75$, $x_3 = 2$, and $x_4 = 3$.

products, and a warehouse for chemical cleaning products. The warehouses' size range between 1500 and 5500 m^2, they all use unit-load for SKUs movement, and they all are use single-deep pallet racking with various storage heights. Two of the warehouses work for 16 h per day while the third works for 10 h per day. For two of the warehouses, the observation period for data collection was about 45 working days, 2–3 h per day distributed over the daily working time; so data from all working conditions were collected. The data of the third warehouse was provided by the company according to their long historical observation. Accordingly, the distributions in Table 1 were estimated based on sample sizes with 100–150 observations.

Below are further assumptions of the adopted warehouse:

- Both the traditional layouts and fishbone layout have front and back cross-aisles while the horizontal layout has only front cross-aisle.
- The picking aisles are two-sided and are wide enough to allow pickers to change direction and also to allow picking on both sides of the picking aisles.
- The P/D point is located in the middle of the front side of the warehouse and all picking and receiving activities take place at the P/D point.
- All SKUs have the same size and 10 SKUs compose one compartment (unit load).
- All functions (picking, storing, etc.) are conducted using a cart that can handle a single compartment.
- All storage locations are identical in size and each location can store one compartment only.
- The storage height and the storage row depth are single compartment.
- The warehouse's working time is 12 h. In the first 4 h, operators can work only in the receiving, unloading, put away and storage. In the last four hours, they work on order preparation, picking and shipping. In the middle four hours, operators can perform all warehouse functions.
- Each function in the warehouse is handled by a single operator.
- Strict-order-picking policy is adopted.
- Three different SKUs categories, A, B and C; are assumed to be stored in the warehouse with orders consist of random mixes from these three categories. Yet, the ABC classification assumes a descending demand with highest demand for category A (50%), moderate for B (30%) and lowest for C (20%). (Table 1 provides the probabilistic details for the received orders (demand) for the three categories)

4.2 *Experimental design*

Table 2 shows the five studied warehouse design components and their levels. The 'throughput or SKU flow' component has four levels where the second level, for example, implies that SKUs are received and shipped to and from the

Table 2. Warehouse design components and their levels.

Component	Levels
Throughput*(SKUs flow)	1. Receiving is Exp(2) h per N(50,10) SKU, and shipping every Exp(2) h per single order (low flow) 2. Receiving is Exp(2) h per N(100,10) SKU, and shipping every Exp(1) h per single orders (medium flow) 3. Receiving is Exp(1) h per N(75,10) SKU, and shipping every Exp(2) h per three orders (high flow) 4. Receiving is Exp(1) h per N(125,10) SKU, and shipping every Exp(2) h per five orders (very high flow)
Size	1. 300 storage locations (small size) 2. 400 storage locations (medium size) 3. 500 storage locations (big size)
Layout	1. Traditional layout 2. Traditional layout with one cross aisle 3. Fishbone layout 4. Horizontal layout
Operational policies	1. Random storage policy with no routing policy (no policies) 2. Volume-based storage policy with traversal routing policy (standard policies)
Manpower/carts	1. Six operators/carts are available (low manpower) 2. Twelve operators/carts are available (intermediate manpower) 3. Eighteen operators/carts are available (large manpower)

*Note that the receiving and shipping functions which are explained in Table 1 are both represented in the throughput component.

warehouse according to the exponential distribution with mean times between receiving and shipping equals to two hours and one hour, respectively. In addition, this level assumes that the amount of received SKUs is normally distributed with mean of 100 SKUs and standard deviation of 10 SKUs while the shipping is conducted for individual orders. The second component is related to the warehouse size with three levels: small, medium, and big; having storage capacity of 300, 400 and 500 storage locations, respectively. Because of the interaction between the diagonal aisles and rectangular shape the storage locations in the fishbone layout were exactly 292, 404 and 484 for the small, medium and big sizes, respectively. These differences are within the ±4% used by Pohl, Meller, and Gue (2011). The third component is related to the warehouse layout with four levels indicating the different warehouses layout alternatives described in Section 4.1. The fourth component has two levels: the first level represents lack of operational policies (random storage policy with no routing policy) while the second level represents common practical operational policies (volume-based storage policy with traversal routing policy) (Caron, Marchet, and Perego 1998; Petersen and Aase 2004; Roodbergen and Vis 2006). Finally, the fifth component corresponds to the utilised number of manpower/carts with low, intermediate and large levels. As a result of the above arrangement, 288 ($4 \times 3 \times 4 \times 2 \times 3$) combinations/experiments have emerged. Simulation experiment for each combination was conducted.

4.3 *Simulation modelling*

Simulation modelling can be implemented through formal modelling such as PN (Basile, Pasquale, and Domenico 2012), CPN (Buil and Miguel 2008), matrix-based framework (Giordano et al. 2008); commercial simulation tools such as ARENA (Altarazi and Ammouri 2010; Ekren et al. 2010; Chan and Hing 2011; Emami, Arabzad, and Sajjadi 2014; Peixoto et al. 2016), ProModel (Dukic, Vedran, and Opetuk 2010), AutoMod (Hwang and Gyu 2006), Enterprise Dynamic (Chackelson et al. 2013), NetLogo (Shqair, Altarazi, and Al-Shihabi 2014); or appropriate programming language such as visual basic (Roodbergen, Vis, and Taylor 2015) and Delphi (Basile, Pasquale, and Domenico 2012). PN is one of the most resourceful modelling tool for discrete-event systems (Mueller 2007), its' models are usually modular and scalable (Basile, Pasquale, and Domenico 2012), and suits large systems with many subsystems (Zhou and Venkatesh 1999). However, researchers on warehouse design via simulation usually prefer to implement commercial simulation tools; implementation of formal modelling approaches, in warehouse design, has been mainly associated with operational control issues. This can be attributed to the higher complexity of the formal model in comparison with the friendly-use of commercial simulation packages. According to Baker and Canessa (2009), more than half of warehouse designers use simulation software during the warehouse design process. ARENA 15.0 software was used in this research. During the last years, ARENA had established a proven track record of enabling companies to model and evaluate supply chains and warehouses (ARENA 2017). Several ARENA-adopted case studies covering supply chain, logistics and retail case studies can be found in (ARENA 2017).

4.3.1 *Model building*

Several modules were developed and integrated together to form the overall ARENA model; entities, resources and storage queues. The entities module consists of three types: stored SKUs entities, order list (picking list) entities and logic entities. The stored SKUs entities describe the SKUs to be stored. The order list entities specify the order with the amount, as in Table 1, of each SKU category to be picked to fulfil an order. The logic entities are used to compute the evaluation performance measure and to initialise the definition of warehouse layout capacity. Attributes are assigned to each SKU entity and order-list entity for identification purposes and to save the entrance time of each SKU to the warehouse. The resources module consists of four types: unloading manpower at each receiving dock, loading manpower who loads the picked SKU to the transporting carts, storing manpower who drives the cart and searches for the best storage location based on the routing policy adopted and picking manpower who receives the order and delivers it from its storing locations to the shipping dock. It is worth mentioning that a resource is capable of handling one compartment per task and that the number of resources varied according to manpower/carts factor levels. Finally, storage queues represent storage locations where compartments are stored.

The model can be viewed in two main parts. The first part models the receiving, unloading, put away, and storage functions. The second part is for order preparation and picking, loading and shipping functions. Figures 2 and 3 present the flowcharts for these two parts, respectively. In Figure 2, stored entity represents the arrival of trucks to the P/D point according to the statistical distribution given in Table 1. The unloading manpower resource unloads the received SKUs, classifies them into the main categories and batches 10 SKUs of the same category together to form a compartment. The compartment remains at the receiving dock, until a storing manpower resource became idle to pick it and store it in a suitable location according to first-come first-serve (FCFS) dispatching rule. If random policy is implemented, the stor-

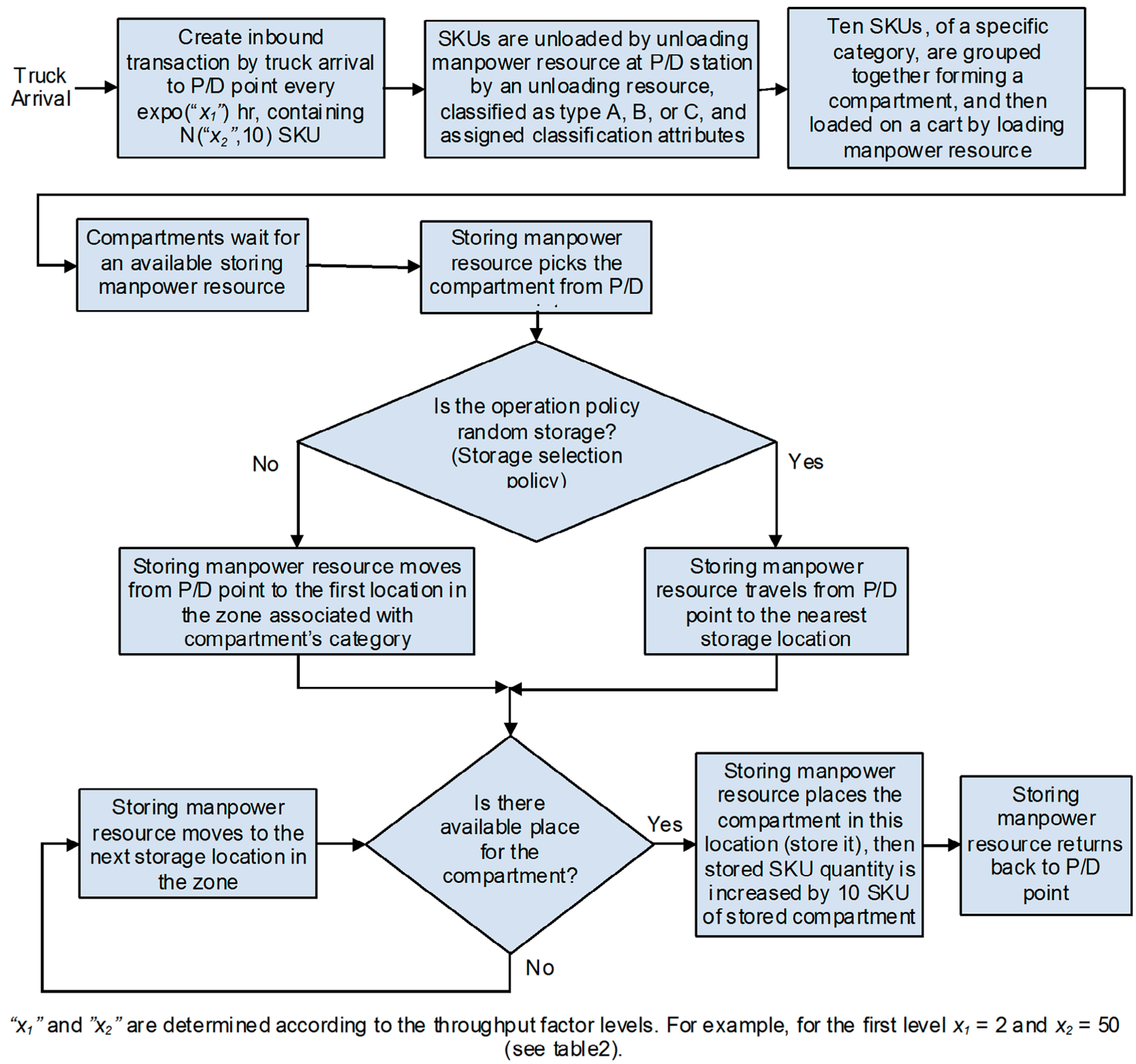


Figure 2. The simulation flow chart of inbound warehouse operations (receiving, unloading, putting way and storing).

ing manpower resource starts searching from the nearest empty location then advances to next locations. When an empty location is found, the compartment is placed there and storing manpower resource returns to the P/D point to pick another compartment. On the other side, if volume-based storage policy is selected; the search starts from the first location of the storage compartment’s category zone.

In the second part of the simulation model (Figure 3), according to the throughput level an outbound transaction is created by the arrival of orders. Next, an order list of the required quantities of each of the main categories (A, B, C) is identified as attributes and assigned to the order entity. Order list is picked by an available picking manpower resource from the P/D point according to FCFS dispatching rule. Based on the adopted operational policies; the picking manpower resource searches for the appropriate SKUs in order to fulfil the order list. If random policy is adopted, the resource starts searching from the nearest storage location. The resource picks the SKUs according to their attribute (quantity of each category). The resource continues searching for SKUs in different location until fulfilling the whole order; accordingly, a single order can be picked from one or more than one storage location. In a volume-based storage policy, the manpower picking resource starts searching for a certain SKU category from the first location of the cate-

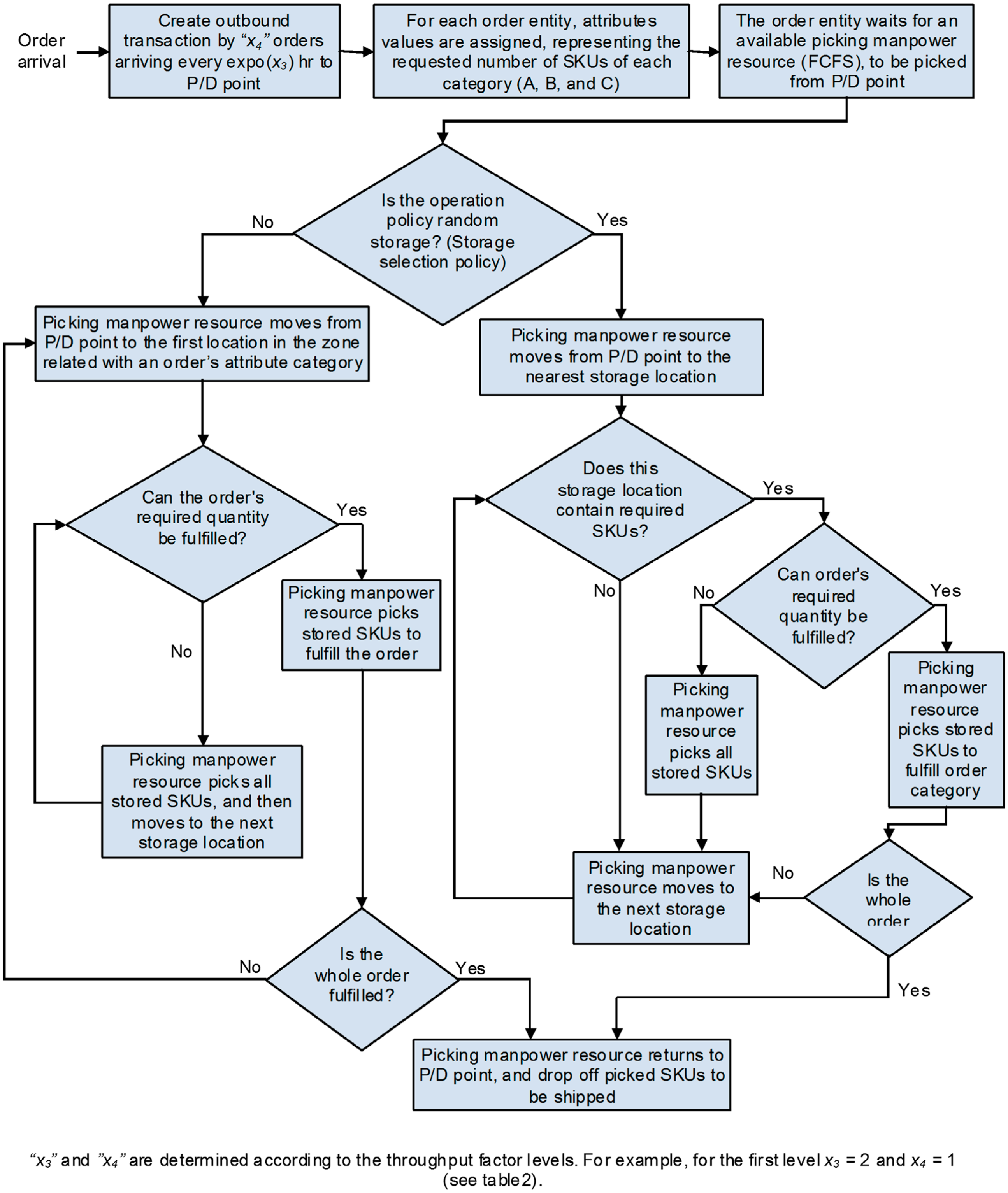


Figure 3. The simulation flow chart of outbound warehouse operations (picking, order preparation and loading).

gory's zone until the whole order is fulfilled. After fulfilling the order, the resource returns to the P/D point for order shipping.

Random variants have been generated for each distribution in each replicate, and stored in external files to be read by the model during the simulation experiments. These files include the replicate input; the time between truck arrivals, the load carried by each truck, the number of arriving items in the order list and times. These files are unique for each simulation replicate and throughput level. These files are used to guarantee identical replicate's random variants in the simulation runs for different experiment scenarios; which insures that in the same replicate number, for an experiment scenario, the same random variates are used. Other experiment scenarios variables include warehouse characteristics such as number of aisles and storage location. These variables vary depending on the experimented warehouse size in the simulation run experiment. Warm-up period has been defined as 10% of simulation run and the model performance was evaluated during the simulation run time after the warm-up period. Throughput levels were defined after finishing the warm-up period and entering steady-state period.

4.3.2 *Model verification and validation*

The model is built as small sub-models and additional logical variables were incorporated accordingly. The model logic was verified through debugging and tracking variables' values. Each sub-model was built and debugged separately, then, the sub-models were integrated and rechecked. Integration continued until the whole model was created.

To validate the model, its behaviour was compared with a real-life warehouse presented in a previous work for the same authors of the current research (Altarazi and Ammouri 2010). In comparison with the design components presented in Table 2, the characteristics of the real-life approximately-rectangular warehouse would be: very high throughput, large size, horizontal layout, random storage policy, strict-order-picking policy, traversal routing and intermediate manpower/carts. The simulation modelling methodology explained in Section 4.3.1 was run for this real-life warehouse considering all the warehouse functions presented in Table 1 (data about these functions for the real-life warehouse and other details about it can be found in (Altarazi and Ammouri 2010). The simulated average cycle time (ACT) per SKU was estimated by the simulation model, then, this simulated ACT was compared with the actual ACT per SKU. Very comparable values were found between the actual and simulated ACT. As a result, the proposed modelling methodology was validated.

4.4 *Performance evaluation*

The ACT for an SKU is the criterion used to assess the performance of the simulation experiments. Equation (1) expresses how the simulation model computes the ACT. Logic entities, assigned attributes and different model variables were used to calculate the ACT.

$$\mathrm{ACT} = \frac{\sum_{i=1}^{i=\mathrm{SKUs}} CT_i}{n} \tag{1}$$

and

$$CT_i = ST_i - ET_i$$

where

CT_i is the cycle time of SKU_i
ST_i is the time once SKU_i is ready for shipment
ET_i is the time when SKU_i enters the warehouse
n is total number of SKUs picked during a simulation run

As can been seen, the ACT is calculated as the average time difference between receiving and shipping SKUs in a simulation run. This time aggregates the times used by all functions listed in Table 1; including SKU unloading, putting away, storing, picking, preparation and loading times. It is worth noticing that most related research includes only the times of picking, preparation and loading to calculate the order-to-delivery time and ignores the times of other functions.

5. Analysis of results and discussions

This section reports the results and analyses generated for the 288 simulation experiments. Table 3 summarises the simulation results. Each result is an average of 20 simulation replications and each experiment consists of 100 h runtime. To interpret the obtained results, several types of analyses were conducted. Analysis of Variance (ANOVA) was used to

Table 3. Simulation-obtained results for ACT (in hours).

			Operational policies					
			No policies			Standard policies		
			Manpower/carts			Manpower/carts		
Throughput	Size	Layout	Low	Intermediate	Large	Low	Intermediate	Large
Low	Small	Traditional	11.76	10.54	11.02	10.68	9.94	9.67
		Trad. with cross aisle	10.68	10.15	9.91	9.60	9.12	9.94
		Fishbone	10.58	11.18	10.46	9.19	8.74	8.02
		Horizontal	10.78	10.97	11.30	9.10	8.50	9.10
	Medium	Traditional	11.98	11.45	12.58	11.02	10.78	9.60
		Trad. with cross aisle	10.97	11.14	9.72	9.60	9.53	9.43
		Fishbone	11.98	11.23	11.50	9.17	9.70	9.34
		Horizontal	12.14	10.97	10.08	9.34	9.12	8.18
	Big	Traditional	10.78	10.27	11.02	10.01	10.42	9.94
		Trad. with cross aisle	11.64	10.78	10.92	10.92	10.10	9.24
		Fishbone	12.48	11.59	11.35	11.02	10.27	9.36
		Horizontal	10.97	10.85	10.82	9.36	9.17	9.07
Medium	Small	Traditional	10.92	9.19	10.08	9.29	7.61	7.90
		Trad. with cross aisle	9.07	9.05	9.60	8.35	7.25	7.01
		Fishbone	10.82	9.72	9.58	8.59	8.45	8.18
		Horizontal	9.24	9.72	9.72	8.52	8.33	8.38
	Medium	Traditional	11.16	10.75	10.13	9.86	8.28	8.14
		Trad. with cross aisle	10.92	10.92	9.77	10.01	9.29	7.73
		Fishbone	10.66	10.51	9.96	10.51	9.07	8.66
		Horizontal	10.99	10.08	10.42	8.93	8.06	7.39
	Big	Traditional	11.02	10.25	9.91	9.07	8.64	8.40
		Trad. with cross aisle	10.85	10.58	10.13	8.47	8.28	7.63
		Fishbone	11.71	10.08	10.27	9.19	8.26	8.28
		Horizontal	10.25	9.62	10.15	9.14	7.49	8.02
High	Small	Traditional	6.34	10.20	9.48	7.51	10.82	7.10
		Trad. with cross aisle	7.32	8.93	8.38	7.27	5.59	6.74
		Fishbone	12.36	10.01	8.54	9.34	9.22	7.87
		Horizontal	9.42	9.31	9.24	9.14	7.48	6.91
	Medium	Traditional	10.18	10.08	9.10	13.34	13.34	12.46
		Trad. with cross aisle	8.62	7.97	8.93	10.37	9.79	9.14
		Fishbone	10.61	10.30	9.26	8.78	9.50	8.23
		Horizontal	9.91	9.70	8.74	8.83	6.86	9.46
	Big	Traditional	13.10	9.65	9.21	11.47	9.02	8.78
		Trad. with cross aisle	11.95	10.61	8.26	9.34	8.86	6.91
		Fishbone	11.40	10.10	9.10	8.86	8.28	8.38
		Horizontal	9.06	8.50	8.26	5.88	5.78	4.61
Very High	Small	Traditional	7.92	9.05	7.25	7.25	7.13	6.82
		Trad. with cross aisle	8.41	8.42	13.92	8.57	6.32	5.70
		Fishbone	10.75	9.31	11.88	10.61	7.58	7.66
		Horizontal	10.85	9.07	7.46	12.17	6.50	8.47
	Medium	Traditional	10.13	9.84	4.78	11.08	9.12	8.18
		Trad. with cross aisle	8.54	8.04	7.34	9.34	8.71	8.13
		Fishbone	10.49	8.98	9.44	10.13	7.32	7.13
		Horizontal	9.29	8.81	6.77	8.90	8.21	6.11
	Big	Traditional	15.71	12.31	8.98	8.66	10.54	6.34
		Trad. with cross aisle	15.02	7.30	7.20	9.53	7.90	6.65
		Fishbone	10.61	8.83	8.47	9.54	8.59	7.43
		Horizontal	9.05	8.95	5.35	9.86	7.97	4.27

identify which warehouse design components (main factors) or components' interaction significantly affects the ACT. Main effect plots and two-way interaction plots were generated to illustrate how levels' means differ and which levels can achieve the best ACT performance. The effects of some of the studied parameters were intuitive. The effects of the throughput interactions with other components, however, were not clear; hence, multi-comparison Tukey's tests were conducted to analyse the effects of these interactions. Minitab statistical package was used for analysing the results.

In addition to the results of the primary 288 experiments, this section also presents the results and analyses of another 288 experiments which were conducted as a sensitivity analysis regarding the key assumption of single SKU in each SKU category. Warehouses' design principles are drawn at the end of the section.

5.1 *ANOVA*

Table 4 shows the ANOVA results. The F-ratio for the five main components, their two-way, and three-way interactions (four-way and five-way interaction effects were neglected) was found by dividing the mean square of the effect of interest by the error mean square. Setting type one error at 0.05, any effect with a P-value less than 0.05 indicates significance. P-values reveal that all single effects, most the two-way interactions, and about half the three-way interactions; are significant. In fact, this two-way and three-way interactions' significance support the argument regarding the necessity for a synthesis warehouse design perspective which, as evidenced by this research, can be enabled by simulation. Figure 4 (a) and (b) further explains the ANOVA results. It is worth mentioning that several residual checking were conducted to validate the ANOVA model (not provided for brevity reasons). The normal probability plot and the histogram for standard residuals have not indicated any deviation from normality, thus, normality assumption was validated. The plots of the 'fitted values' and 'observation order' against the standard residuals demonstrated the randomness of residuals. Hence, it could be assumed that variability is independent for both 'fitted values' and 'observation order'. Finally, from last two plots, variability was verified constant with respect to both variables.

Explaining the effects of operational policies and utilised number of manpower/carts is straightforward. Adopting volume-based storage and traverse routing, in comparison with random storage and no routing policy; is translated into a decrease in the ACT. In fact, several previous studies have resulted in similar results including (Petersen and Aase 2004). Similar to the effect of adopting 'standard policies', an increase in the number of manpower/carts directly turned

Table 4. Full factorial ANOVA for the ACT results.

Source	DoF	Seq SS	Adj MS	F ratio	P-value
Throughput	3	100.5	33.5	35.69	0.000
Size	2	14.6	7.3	7.82	0.001
Layout	3	41.0	13.6	14.55	0.000
Operational policies	1	122.4	122.4	130.32	0.000
Manpower/carts	2	81.1	40.5	43.21	0.000
Throughput × Size	6	15.1	2.5	2.68	0.017
Throughput × Layout	9	15.8	1.7	1.87	0.062
Throughput × Operational Policies	3	8.3	2.7	2.97	0.034
Throughput × Manpower/carts	6	27.7	4.6	4.92	0.000
Size × Layout	6	30.7	5.1	5.46	0.000
Size × Operational Policies	2	12.8	6.4	6.82	0.002
Size × Manpower/carts	4	16.3	4.0	4.35	0.002
Layout × Operational Policies	3	6.7	2.2	2.39	0.072
Layout × Manpower/carts	6	3.3	0.5	0.60	0.729
Operational Policies × Manpower/carts	2	0.8	0.4	0.45	0.637
Throughput × Size × Layout	18	42.8	2.3	2.53	0.001
Throughput × Size × Operational Policies	6	19.3	3.2	3.44	0.003
Throughput × Size × Manpower/carts	12	21.6	1.8	1.92	0.037
Throughput × Layout × Operational Policies	9	19.7	2.1	2.33	0.018
Throughput × Layout × Manpower/carts	18	23.4	1.3	1.38	0.149
Throughput × Operational Policies × Manpower/carts	6	0.7	0.1	0.14	0.991
Size × Layout × Operational Policies	6	12.1	2.0	2.15	0.052
Size × Layout × Manpower/carts	12	12.9	1.0	1.15	0.328
Size × Operational Policies × Manpower/carts	4	9.6	2.4	2.57	0.041
Layout × Operational Policies × Manpower/carts	6	3.3	0.5	0.59	0.741
Error	132	124.0	0.9		
Total	287	787.7			
$S = 0.969286$ $R^2 = 84.26\%$ $R^2(\text{adj}) = 65.77\%$					

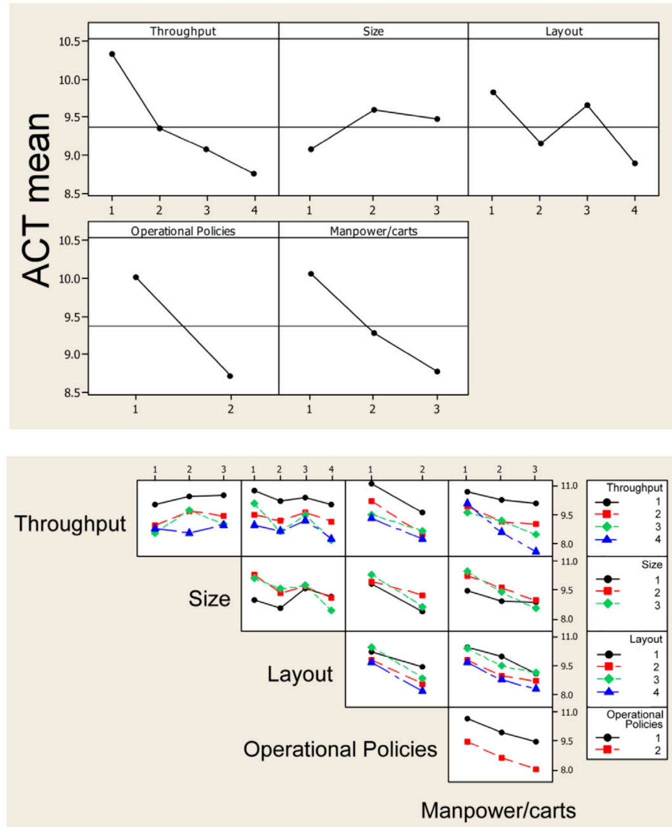


Figure 4. (a) Main effects' and (b) Two-way interaction effects' plots for the ACT. (Components' levels are similar to what listed in Table 2, for example level 3 for the throughput means 'high' throughput).

into a decrease in the ACT. This was expected since more resources means less number of order to pick per resource, or less average number of SKUs in orders; which means better warehouse performance or less ACT.

Regarding the throughput (SKUs flow) component, Figure 4(a) shows that as throughput increases the ACT decreases. This is mainly because high throughput may cause high SKUs percentage to be cross-docked. This cross-docking behaviour implies going directly from put away to loading, skipping the storage delay, and reducing the time of the picking function; accordingly, reducing the ACT. With lower throughput levels, SKUs go through all warehousing functions resulted in higher ACT.

Considering the size component, Figure 4(a) shows that the best ACT can be achieved by the smallest warehouse size regardless, mostly, the status of other components (as can be seen from Figure 4(b)). Intuitively, since increasing the warehouse size results in an increase in the putting away and picking routes' distances; it will cause ACT to increase. Medium and large warehouse designs resulted in higher ACT (this is also shown in Figure 6 for the 10 SKUs scenario presented in Section 5.3). In fact, Figures 4(a) and 6 show that the superiority in ACT is not always toward one of these two sizes. This contradiction is revealed in Figure 4(b); the ACT performance of medium and large sizes differs based on the status of other components levels. For example, large size results in better ACT when standard operational policies are implemented. In real life, adopting the above results can help the proper fit of supply chains on the efficiency–responsiveness spectrum. That is, a small size warehouse is recommended for achieving better supply chain responsiveness.

For the warehouse layout design component, traditional layout produced the worst ACT; yet adding a cross-aisle, that is the two-block layout, has enhanced the ACT. Actually, this result confirms literature findings (Roodbergen and Koster 2001; Shqair, Altarazi, and Al-Shihabi 2014); however the current study confirmed that this result is still valid taking into consideration more design components than those considered in literature and regardless of the levels of these design components. Statistically, fishbone layout shows a comparable performance with the traditional layout as seen from Figures 4(a) and 6. Interestingly, the horizontal layout generated the best ACT regardless of the status of other design components, as seen in Figure 4(b), and even with the 10 SKUs scenario as in Figure 6. This result can be allied to the fact that the distance travelled in the horizontal layout is less than that in other layouts, that is, cross-aisle travelling in the horizontal layout allows the picker to start picking items in the second section immediately while extra travelling would be required, for example, in traditional layout (Caron, Marchet, and Perego 2000).

Figure 4(b) plots the interaction effects between each pair of the five components. As also indicated by the *P*-values in Table 4, some pairs involve no significant interaction. For instance, no interaction exists between operational policies and manpower/carts, that is, standard operational policies are always better than random policies regardless of the manpower/carts level. Similarly, no interaction exists between layout and manpower/carts. This was expected since changing the manpower/carts won't affect the travelled distance if the layout has changed. On the other hand, most of the interactions are significant; such as the throughput-size, throughput-layout, throughput-manpower and size-layout interactions. Some interactions' effects is understood, for example, the reduction in travelling distance associated with horizontal layouts is more significant with large warehouses sizes than with small and medium sizes; hence interaction effect exists for the size-layout resulting in different ACT performance of small size comparing to other sizes when layout varies. However, the effect of other interaction is not clear. Examples of such cases include the throughput-size and throughput-layout interactions. Tukey's tests were implemented to reveal these issues.

5.2 *Tukey's multi-comparisons tests*

Tukey's tests were performed to reveal what throughput's levels do interact with the levels of other design components. Before presenting the test results, it is worth mentioning that the Tukey's-tested simulated data were verified to confirm the test's assumptions including data independency within and between samples (this was guaranteed by the simulation experiments), normally distributed data and homogenous variance across the samples (normal probability plots were generated to validate these two assumptions).

Figure 5(a) and (b) summarises the results of Tukey's tests. Bold lines were to present the test results with two bases: (1) the compared configurations are ranked in ascending order with respect to the ACT performance (lower ACT

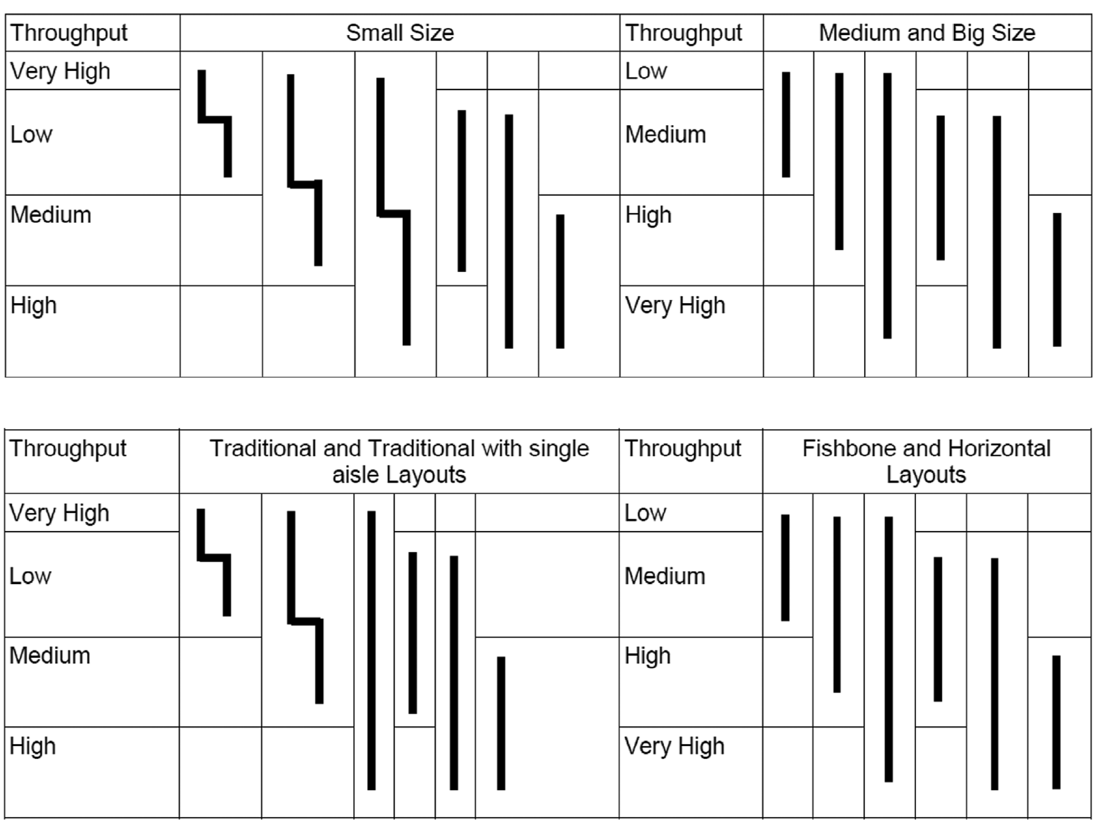


Figure 5. Tukey's tests for (a) throughput by size and (b) throughput by layout.

indicates better performance) and (2) if the difference between two configurations (with respect to ACT) is insignificant the bold line will be straight. For example, in Figure 5(a) for the 'throughput small size' comparisons: (1) the ascending order for the throughput levels according to the ACT is 'very high', 'low', 'medium', and 'high'; (2) the 'very high' throughput level has significantly higher ACT performance than all the other three levels while all the other three levels are statistically indifferent from each other, hence, their tests are represented by a straight bold lines.

Figure 5(a) shows that small warehouses can significantly reduce the ACT only when the throughput is 'very high'. That is, it seems that the cross-docking practice is more applicable in small warehouses sizes; on the other hand, with medium and large warehouses high inventory would be available and stored SKUs would be used to fulfil the orders instead of the just-arrived SKUs.

Figure 5(b) illustrates that no difference in ACT performance is achieved for different throughputs levels for the horizontal and fishbone warehouse layouts. However, traditional layouts, either with or without cross-aisle, performs better when the throughput level is very high. In other words, traditional layouts performance is enhanced with very high-throughput level while other layouts' performance does not. Because traditional layout encloses the highest travelled distance among other layouts, it is the most affected by high throughput. On the other hand, high throughput would have lower effect on other layouts since their travelled distance, comparing to traditional layout, are originally lower.

5.3 *Single vs. multiple SKU per each SKU category*

Sensitivity analysis was conducted to test the effect of number of SKUs within each SKU category. The original model, called here the three SKUs scenario, explained in Section 3 assumes that each SKU category (A, B and C) consists only of a single SKU type. In practice, a number of SKUs types can be found within each SKU category, hence requiring different storage locations for each type but within the category's specified space (as shown in Figure 1). Simulating all scenarios of 'what SKU types can be included in each category' is not viable. Hence, for demonstration purposes a scenario, called the 10 SKUs scenario, of 2, 3 and 5 SKUs types in categories A, B and C, respectively; was simulated for the whole 288 combinations. The simulation results (not provided for brevity reasons) for the new 288 experiments of the 10 SKUs scenario showed higher ACT values than the three SKUs scenario. This was expected since more routing in the 'picking' and 'putting away' functions are required for the 10 SKUs scenario.

Full ANOVA analysis was performed for the 10 SKUs scenario. Main effects plots are given by Figure 6. Except for some of throughput's interactions; significant main factors, interactions and optimum levels were found similar to what found in the three SKUs scenario. The dominance performance for very high throughput and small size's warehouses are still valid, however, Figure 6 clearly shows that there is a throughput limit above which different throughput levels become insignificant in affecting the ACT. As explained before, cross docking can be behind the low ACT for the very high-throughput small size design configuration. The ACT performance enhancement of the low throughput level in the 10 SKUs model, which is very comparable to medium and high levels while it was much worse in the 3SKUs scenario; can be attributed to the larger number of SKUs a picker can pick in a single trip comparing to the three SKUs scenario.

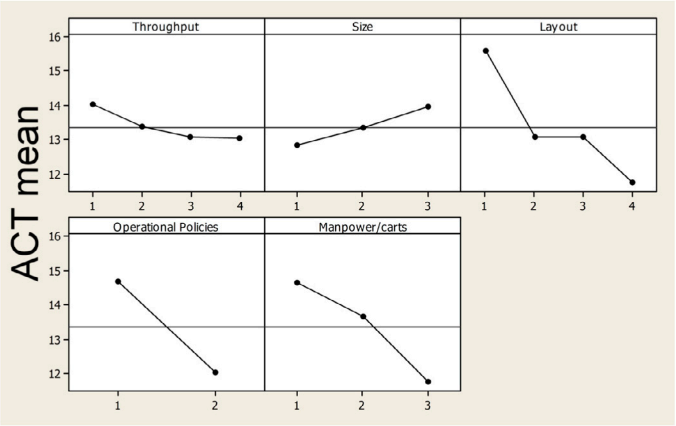


Figure 6. Main effects' plots for the ACT for the 10 SKUs scenario.

5.4 *Warehouses' design principles*

Based on the above analyses, the following principles for manual-order-picking warehouse design can be suggested.

- In general, the following design components produce the best ACT performance: horizontal layout, very high throughput, standard operational policies, large manpower/carts and small size.
- In supply chains with uncertain throughput scenarios, the ACT performance can be enhanced by going to very high-throughput level if the warehouse size is small and/or layout is traditional with or without aisle.
- If it is viable in the case of medium throughput levels, it is recommended either to sum more throughputs into one big size warehouse or to split the throughput and allocate it to two small warehouses.
- For traditional warehouse layout, adding a cross-aisle will improve the warehouse performance.
- Even for low throughput-small size warehouses, volume-based storage policy with traversal routing policy is better than 'random storage policy with no routing policy'.
- The above guidelines are valid for single or multiple SKU per each SKU category. Yet, as the number of SKUs per SKU category increases the ACT increases.

It is worth noticing that these guidelines are only applicable within the assumptions and considerations of the current study. For example, in case of changes in the levels of the design components, different statistical distributions of warehouse functions, non-rectangular shape of the warehouse, multiple-floor warehouse, double-deep racks and any violation of assumptions stated in Section 4.1; then the resulted guidelines could be infeasible. Additionally, as those guidelines were resulted based on the ACT performance, they could be invalid if other performance criterion, such as space utilisation, was utilised.

6. Conclusions and future work

This study presented a concurrent DoE-simulation modelling approach for the manual-order-picking warehouse design problem. Warehouses' throughput, size, layout, manpower/carts, and operational policies were the five design components incorporated in the simulation model. Warehousing key functions of receiving, unloading, put away, storing, order preparation and picking, loading and shipping; were all included also. The total time an SKU spends in the warehouse was utilised to evaluate the warehouse performance. SKUs were divided into three categories with different demand levels. Two scenarios of 'number of SKUs per an SKU category' were simulated, each with 288 design combinations. Thorough statistical analyses for the simulation results of the two scenarios were conducted and the following key findings were concluded:

- Horizontal layout is preferable over all other studied layouts.
- In general, small size warehouses perform better than larger sizes.
- Adding an aisle to a traditional layout improves its performance regardless of other design components' situation.
- Higher throughput is recommended for traditional layout-small size warehouses.
- Compromising should be implemented between the number of SKUs in a warehouse and its ACT performance.

Finally, the current research emphasises the need for concurrent warehouse design-oriented studies taking into consideration the probabilistic nature of all warehouses' functions and an external customer performance evaluation. Directions for future research include extending the design components levels; for example to consider more size and throughput levels, other operational policies, and other layouts alternatives. Incorporating more warehouse design issues such as the storage method utilised, and the size of unit load could also be done. It is also worth investigating to consider multi indicators for the warehouse performance, for instance, to consider in addition to cycle time the utilisation of warehouse space, manpower and material handling equipment. A multi-objective analytical optimisation modelling for the warehouse design problem is another area to be investigated. Finally, it would be interesting to explore implementing PN as a simulation formal model for the concurrent warehouse design problem.

Disclosure statement

No potential conflict of interest was reported by the authors.

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