International Journal of Production Research

ISSN: 0020-7543 (Print) 1366-588X (Online) Journal homepage: https://www.tandfonline.com/loi/tprs20

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To cite this article: Y.K. Tse , K.H. Tan , S.L. Ting , K.L. Choy , G.T.S. Ho & S.H. Chung (2012) Improving postponement operation in warehouse: an intelligent pick-and-pack decision-support system, International Journal of Production Research, 50:24, 7181-7197, DOI: 10.1080/00207543.2011.643505

To link to this article: https://doi.org/10.1080/00207543.2011.643505

Published online: 31 Jan 2012.

International Journal of Production Research
Vol. 50, No. 24, 15 December 2012, 7181–7197

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Improving postponement operation in warehouse: an intelligent pick-and-pack decision-support system

Y.K. Tse[a]*, K.H. Tan[b], S.L. Ting[c], K.L. Choy[c], G.T.S. Ho[c] and S.H. Chung[c]

[a]*The York Management School, University of York, Heslington, York, UK;* [b]*Nottingham University Business School, Jubilee Campus, Nottingham, UK;* [c]*Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Kowloon, Hong Kong*

(*Received 10 December 2010; final version received 18 November 2011*)

Today, many manufacturers prefer to shift their pick-and-pack postponement operations to third-party logistics companies to lower operational cost and improve mass customisation flexibility. The type of pick-and-pack operation is complicated, as it usually involves a large number of stock keeping units and several warehouse operations. Surprisingly, in most 3PL, the complicated postponement operations are still mainly managed by an experienced warehouse manager, which is an unreliable methodology and often creates many mistakes. A hybrid intelligent system integrating Case-Based Reasoning and Fuzzy Logic is proposed to support the manager in making pick-and-pack postponement decisions. The system comprises a solution-refining module that proposes and holds the details of past pick-and-pack operations. This approach will be of benefit to managers as effective decision support of pick and pack planning can be provided. A case study is used to illustrate the applicability and effectiveness of the approach. Implications of the proposed approach are discussed, and suggestions for further work are outlined.

Keywords: intelligent systems; postponement; picks and pack operation; 3PL

1. Introduction

In recent years, many firms have shifted their postponement activities to third-party logistics companies (3PL). In 2010, more than 40% of clients outsourced their postponement activities, which include assembly, labelling, and packaging to 3PL in the Asia Pacific region (3PLStudy 2011). Firms tend to outsource the postponement activities to 3PL, as the firms are able to (1) achieve a better customisation level, (2) reduce costs in supply-chain operations, (3) enhance the flexibility of the postponement process, (4) reduce distribution centre/transit inventory costs, (5) eliminate factory inventory costs, and (6) shorten the response time (Feitzinger and Lee 1997, van Hoek and van Dierdonck 2000, Shao and Ji 2008). In addition to an increased demand for outsourcing, 3PL needs to perform a wide range of postponement activities with different clients from various industries that involve different customisation criteria. Therefore, a considerable challenge for 3PL is how to plan accurate and efficient postponement activities with a wide range of products (van Hoek and van Dierdonck 2000, Chow *et al.* 2007).

In 3PL, these postponement activities are treated as a kind of 'industrial added value' service to clients, and commonly referred to as *pick-and-pack* (PnP) operations. The PnP service involves a sequence of operations from the disassembly and pick of the required SKU from the original package, then to other processes, such as the light assembly, configuration, adding manual, labelling, sizing, blending and mixing, adding product features, packaging operation, and invoicing (van Hoek and van Dierdonck 2000, van Hoek 2001). As in many warehouse operations, the solution to PnP operations is a combination of several decisions of warehouse operations. For example, the logistics coordinator needs to (1) decide the appropriate layout of the assembly process (i.e. perform the operations on a conveyor belt or a bench), (2) define the operation tasks (i.e. assembly number of parts and packages), (3) manage the sequence of these tasks, (4) estimate the operation time, and (5) allocate the number of crew on the 'shop floor' (Poon *et al.* 2009).

The logistics planner generally bases their approach on past experience to determine how resources are utilised in a PnP operation. In order to obtain an effective solution plan, the logistics planner needs to have a thorough understanding of how the different components and operations interact in terms of trade-offs and the total cost to

*Corresponding author. Email: mike.tse@york.ac.uk

ISSN 0020–7543 print/ISSN 1366–588X online

http://dx.doi.org/10.1080/00207543.2011.643505
http://www.tandfonline.com

the organisation (Chow *et al*. 2007). This 'experience-based' planning approach does not often work out effectively, as the planner does not make appropriate use of their knowledge and experience of previous PnP solutions, instead selecting an easy or recently chosen solution. Moreover, the poor planning of one PnP operation can lead to low efficiency in the entire operation and can even delay the whole shipment. Therefore, a systematic approach is necessary to address operational problems. To begin resolving the operational issue, this paper addresses the question: how could logistics planner retain and reuse their knowledge of previous successful PnP solutions to support outsourced postponement activities?

In this decade, intelligent systems have become an advanced approach for solving highly complicated problems in supply chains, by capturing experts' knowledge and providing decision-making support for managers to plan the logistics and warehouse solutions in a fast and reliable manner (Choy *et al*. 2003, Chow *et al*. 2006, 2007). A review of the literature shows that an intelligent system, such as case-based reasoning and fuzzy logic, can provide many benefits to managers, such as providing consistency in decision-making, support knowledge reuse and retention, as well as yielding instantaneous decision support (Tan *et al*. 2006). Furthermore, intelligent systems have received significant attention in logistics flow, which plays an important role in enhancing logistics service and quality (Chow *et al*. 2006, Poon *et al*. 2009).

The objective of this research is to develop the Intelligent Directed Pick-and-pack System (IPPS) in order to support the postponement activities in 3PL. This research is the first attempt to develop a decision-support system in providing postponement support in 3PL and real-time resource planning solution for the warehouse 'shop floor'.

The rest of this paper is organised as follows. Supportive literature is presented in Section 2. The construct of the proposed IPPS is described in Section 3. In Section 4, a case is used to illustrate the application of the proposed approach. Finally, the results are outlined, and implications of this research for industrialists and academics are discussed.

2. Related studies

2.1 *Postponement operations in warehouse*

The concept of postponement was first documented in the marketing literature in the 1950s (Alderson 1950) and extended to logistics in the late 1980s (Zinn and Bowersox 1988, Zinn 1990). Lee and Billington (1994) defined postponement as a strategy in which the final configuration of a finished product is delayed as much as possible, usually until the customer places the order.

By adopting this strategy, the 3PL performs such light manufacturing and helps the clients comply with the local content rules that are prevalent in emerging markets (Feitzinger and Lee 1997, van Hoek and van Dierdonck 2000). By moving the mass customisation process to 3PL, the firm can have a prompt response to a customer's order. The customised products are assembled and shipped from 3PL, rather than from the manufacturing site which is far away from the destination. In addition, manufacturers can concentrate production to a few sites and benefit from economies of scale (Lee and Billington 1994, Feitzinger and Lee 1997, van Hoek and van Dierdonck 2000). In general, the postponement practices range from packaging and labelling, adding product features, adapting product to final assembly (Zinn 1990, Feitzinger and Lee 1997, van Hoek and van Dierdonck 2000). High value-added postponement activities are seldom outsourced to 3PL, as they lack the necessary expertise. Only minor customisation is performed by 3PL, mainly involving the localisation (the product is localised to fit the regional features) and packaging, as the assembly process in some medium-/high-technology products may require technical skills that warehouse operators may not have (van Hoek and van Dierdonck 2000).

2.2 *Intelligent systems*

An intelligent system is a decision-support tool that is mainly based on AI methodologies to provide a feasible solution in solving real-life problems (Tan *et al*. 2006). In practice, Negnevitsky (2005) suggests that an intelligent system should assist humans in making decisions, searching for information, and solving complex objectives in some narrow areas of expertise.

Each AI approach has its own unique strengths but only identifies feasible solutions for a given situation subject to specific assumptions (Tan *et al*. 2006). For example, CBR provides a similar problem-solving approach to humans by retrieving a successful previous solution. FL is the most useful decision support technique for

Table 1. Research of an intelligent system in supply-chain management areas.

AI techniques employed	Areas	Authors
CBR	Support special operation procedure in warehousing	Chow *et al.* (2006)
CBR	Warehouse resource management	Poon *et al.* (2009)
CBR	Product configuration	Tseng *et al.* (2005)
FL	Auto-warehouse crane system	Li and Lee (2001)
FL	Inventory management	Pan and Yang (2008)
FL	3PL evaluation and selection	Liu and Wang (2009)
FL	Leanness assessment	Vinodh and Balaji (2011)
FL and CBR	Vender selection and order allocation	Faez *et al.* (2009)
FL and CBR	Sales forecasting in print circuit board industry	Chang *et al.* (2008)

considering vague parameters in decision-making. Table 1 shows some examples of intelligent systems in the literature.

2.2.1 *Case-based reasoning (CBR)*

In CBR, new engineering problems are solved by referring to similar cases in the past and adapting to suit the new case. It consists of four main steps – retrieve, reuse, revise, and retain – and forms a continuous improvement cycle by storing successful cases (Aamodt and Plaza 1994). As shown in Table 1, CBR has been broadly adopted in industrial applications primarily owing to its self-learning capability and the characteristics of acquiring memory being similar to human beings (Chow *et al.* 2006). Poon *et al.* (2009) adopted CBR in a logistics resource management system where past memory could be consulted in order to identify similar solutions for handling picking orders in warehouses. Chow *et al.* (2006) proposed a CBR-based warehouse-management system to assist in selecting appropriate sets of resources in various operations. Moreover, Tseng *et al.* (2005) proposed a CBR system to assist BOM planning in differentiating products in mass customisation. The CBR product configuration approach helped to reduce the time to create BOM and offer RandD staff an accurate direction to follow. In sum, CBR techniques can avoid loss of knowledge, and prevent repetition in making mistakes when solving similar problems.

2.2.2 *Fuzzy logic (FL)*

Problem-solving in logistics and warehouses are typically less-structured problems coupled with the presence of complexities and uncertainty. With these problems, there is often some degree of uncertainty about the desired state, and the objective is not clear (Chow *et al.* 2006, Toivonen *et al.* 2006). In such situations, FL is an appropriate technology to substitute for human expertise, when needed to make a choice. For example, Liu and Wang (2009) proposed a fuzzy evaluation approach in selecting a 3PL provider. FL is adopted to make judgements in ranking and screening processes, which often involves uncertain, imprecise, and subjective judgement. Also, FL can be adopted in decision-support models to reflect real-world phenomena. For example, Pan and Yang (2008) developed an integrated model in which the concept of fuzziness is applied to simulate the uncertainties of annual demand and production rate in a real supply-chain system.

These AI approaches are capable of addressing applications efficiently. Each has inherent strengths, but only limited to narrow areas of expertise (Robinson and Malhotra 2005, Che 2010). In this decade, there has been a trend towards integrating more than one AI technique in an intelligent system to solve problems of high complexity. This integrating approach can improve the strengths of individual AI techniques and lessens their drawbacks (Robinson and Malhotra 2005, Che 2010). For example, although CBR's users can relate better to case examples, rather than drawing conclusions from their context, the feasibility of the revised case still depends on the adaptation process (Cheng 2003). To deal with this problem, Faez *et al.* (2009) proposed a vendor selection model that includes both FL and CBR techniques. FL is employed for improving the represented case whose attributes have an imprecise and vague value. Chang *et al.* (2008) adopted the FL technique to improve the accuracy of retrieving similar solutions in the case repository. In sum, FL can be a useful tool to deal with problems when the information of a case solution is imprecise and vague (Vinodh and Balaji 2011).

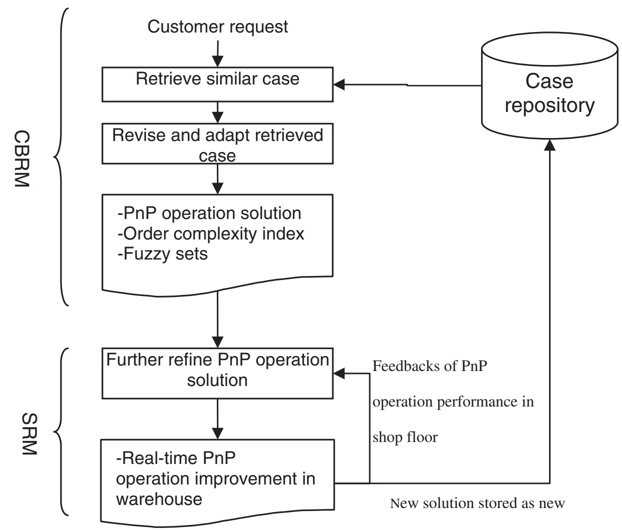

Figure 1. Infrastructure of IPPS.

3. Construct of the intelligent directed warehouse operation system

The infrastructure and data diagram of the proposed IPPS are shown in Figure 1. Holistically, the IPPS consists of two major modules: the case-based reasoning module (CBRM) and the solution refining module (SRM).

The principle of CBRM is that CBR technology is used to provide an initial starting point for the PnP operation plan stemming from similar past requests. There are two major steps in CBRM: (1) the initial PnP operation solutions are retrieved from the case repository; and (2) the retrieved solution is revised by adjusting parameters. The operations are divided into several sub-processes, based on different classes, that are related to the experience of similar problems that occurred in previous cases.

The solution-refining module (SRM) is then used to refine the solution. The SRM adopts FL for adjusting the labour resource allocation of the proposed logistics solution. These parameters are the system input values, and therefore input membership function values can be obtained through fuzzification. The output membership values can be produced through a set of IF–THEN rules. In the stage of defuzzification, the system output value can be acquired by choosing a suitable defuzzification method. Moreover, the SRM is a closed-loop process and so has the ability to continuously improve the PnP solution.

3.1 *Case-based reasoning module (CBRM)*

In this research, CBR approach is adopted in CBRM to assist 3PL in formulating PnP strategies that result in the highest possible customer satisfaction level, with the added benefit of reducing operation costs. The service policy and order requirements are entered into the CBR engine to retrieve a list of past similar cases. The logistics planner then selects the most appropriate case and makes some adjustments to the solution to fit the actual situation. Figure 2 shows the structure of CBR used in this module.

3.1.1 *Case representation*

A case represents specific knowledge associated with a context. It records knowledge at an operational level. It is a contextual piece of knowledge representing an experience. The description of the problem is a number of specification parameters describing the problem that the 3PL is facing. The solution part consists of a workflow diagram, standard operation procedures, level of service complexity, and estimation of operation time in the warehouse workflow, and resource-allocation information such as the staff, facilities, working areas, etc.

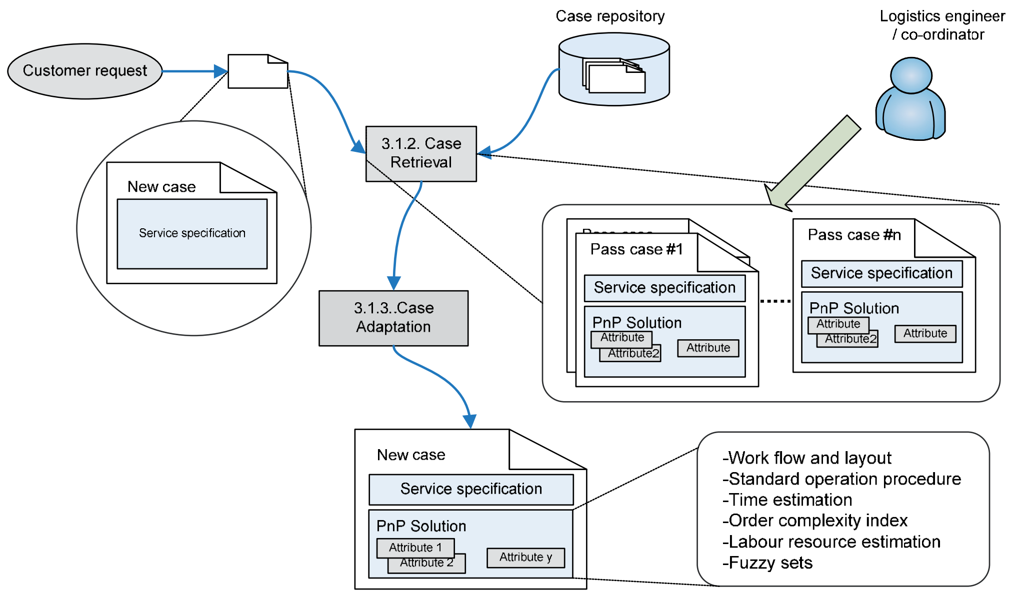

Figure 2. Structure of CBRM.

3.1.2 *Case retrieval*

After the logistics planner enters the query by assigning values to the service attributes, the CBRM starts to retrieve the similar case in the repository. Mathematically, each case is represented in the following notation:

Let Ω_E be the set of all cases, Ω_A be the set of all problem features, and Ω_D be the set of all PnP solutions (i.e. the solution attribute), where each case $c \in \Omega_E$, each attribute $a \in \Omega_A$, and each solution $d \in \Omega_D$. Thus:

$$c = (A_c, D_c), \tag{1}$$

where $A_c \subseteq \Omega_A$ is the set of problem features observed in case c. The set $D_c \subseteq \Omega_D$ is the set of solutions for this case.

PnP solution records are codified and stored as cases in a knowledge base for case retrieval. The present study employs a similarity measure approach, nearest-neighbour retrieval (NNR), for determining the degree of similarity between the new case and old case. During the comparison, the features of a new case are matched to their corresponding features of all cases stored in the knowledge base. The algorithm of case retrieval is shown in Figure 3, and the similarity for each case is calculated using Equations (2) and (3):

$$\text{similatity } (c^I, c^R) = \frac{\sum_{i=1}^{n} w_i \times sim(a_i^I, a_i^R)}{\sum_{i=1}^{n} w_i} \tag{2}$$

$$sim(a_i^I, a_i^R) = \begin{cases} 0 & \text{if } a_i^I \text{ and } a_i^R \text{ are categorical and } a_i^I \neq a_i^R \\ 1 & \text{if } a_i^I \text{ and } a_i^R \text{ are categorical and } a_i^I = a_i^R \\ \dfrac{a_i^R}{a_i^I} & \text{if } a_i^I \text{ and } a_i^R \text{ are numerical and } a_i^I > a_i^R \\ \dfrac{a_i^I}{a_i^R} & \text{if } a_i^I \text{ and } a_i^R \text{ are numerical and } a_i^I < a_i^R \end{cases}, \tag{3}$$

where c^I and c^R represent the new case and the old case respectively, a_i^I and a_i^R represent the ith feature value of the new case and the old case respectively, the similarity function $sim(a_i^I, a_i^R)$ computes the similarity between a_i^I and a_i^R, and w_i represents the feature weighting for each ith feature.

As a result, a unique PnP solution is generated as the suggestions of CBRM.

Input: Examination data of pick and pack problem (postponement operation) determined by the logistics planner
Output: A set of pick and pack operation solution

Preprocessing

Set the weightings w_i for each ith feature

Case retrieval algorithm
Do while (a new case is ready)
Trigger Similarity Analysis
Compute similarity for each cases in the knowledge base
End Trigger
Sort the cases by their similarities in descending order
Extract the pick and pack operation solution list from the retrieved cases
End Do
Report the results

Figure 3. Algorithm of cases retrieval in IPPS.

3.1.3 *Case adaptation*

Adaptation is the process of adjusting the retrieved cases to fit the current case. Adaptation looks for prominent differences between the retrieved case and the current case, and then applies formulae or rules that take those differences into account when suggesting a solution (Shin and Han 2001). Moreover, derivational adaptation is employed in this module. It reuses the rule or formulas that generated the original solution to produce a new solution to the current problem. In this method, the planning sequence that constructed the original solution must be stored as an additional attribute of the case.

3.1.4 *Order complexity index*

The aim of the order complexity index (I_c) is to identify the level of complexity of the service specification. In the solution part of the case, the workflow of the PnP operation procedures will be itemised. The order complexity index is described as:

$$I_c = q \times u \sum_{j=1}^{m} P_j, \tag{4}$$

where m is the set of operation procedures of the order, j is the index number of the procedure, P_j is the complexity index of task j, q is the quantity required by the customer, and u is the stock-keeping unit (SKU) type index. Table 2 shows some examples of tasks in PnP operations.

The indices of task of PnP are defined by the logistics coordinator. Each operational procedure is assigned a complexity index according to the complexity of the procedure that is related to the product type and dimensions. The SKU type index indicates the difficulties of handling different types of products (i.e. fragile, heavy, electronic discharge, food, etc.). The quantity of products will affect the complexity of service; therefore, the quality is also a factor affecting the order complexity index.

3.2 *Solution refining module (SRM)*

After the most appropriate PnP solution is retrieved by the CBRM, the solution is transferred to the SRM for fine tuning. SRM refines the solution by adjusting labour-resource allocation using multi-valued FL. The allocation of

Table 2. Task examples in PnP operation.

Tasks in PnP operation
Removing original package
Disassembling from original package
Light assembly (with bolt)
Light assembly (without bolt)
Outer packaging (fold the box)
Outer packaging (wrap with plastic film)
Internal packaging (plastic bag)
Internal packaging (fold the card board)
Bubble wrap
Gift wrap
Attach tag (e.g. company logo, expiry date)
Attach barcode label
Additional edge protector (e.g. foam protector)
Pack with plastic strap (with machine)
Seal with glue gun
Seal with tape

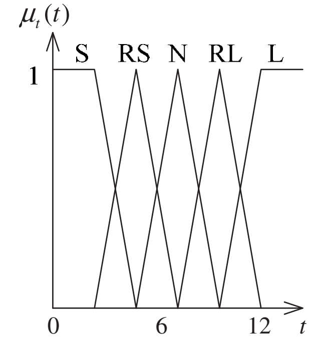

Figure 4. Fuzzy set in SRM.

labour resource in PnP operation is not always planned very precisely, and there is no exact rule to follow for the logistics coordinator and crew supervisor.

The FL decision approach adopted in the SRM refers to works from Negnevitsky (2005) and Lau *et al.* (2008). A solution-refining engine, which consists of a fuzzy set, fuzzy rule, fuzzy inference, and a knowledge base, is embedded in this module. The knowledge base contains the domain knowledge, which includes a number of rules stored in an object-oriented structure. It is used for quality problem-solving and for remedial action when a performance problem is formed. With a good understanding of the rules of customer requirements and of the complexity of service order, it is possible to apply the rules to transform bytes of data into information, and attain an improved solution.

The required knowledge for building up a fuzzy system is collected and extracted from the related domains followed by a procedure to convert it into fuzzy rules, which are stored in the system repository. Moreover, the IF–THEN rules can be retrieved by conducting interviews with domain experts

3.2.1 *Fuzzification*

Fuzzification is the first step of operation in SRM. The crisp input will be converted into a fuzzy value in this process.

In order to carry out this fuzzification process, it is necessary to specify two decisive factors – universe of discourse and membership function – both of which are needed to determine the overall features of the fuzzy sets. The universe of discourse is the numerical range of the inputs, normally referring to the range of the x axis in the graph of the fuzzy set. It limits the range of the input values that are to be constrained within the specified range (Leung *et al.* 2003, Lau *et al.* 2006). The input ranges are subsequently determined in accordance with the analysis results obtained from the collection of data knowledge. The membership function decides the characteristics of the fuzzy subset A:

$$A = \sum_{i=1}^{n} \mu_A(x_i) \tag{5}$$

This equation is the general mathematical expression of fuzzy subset A of X, where X is the whole data set and x is an element of subset A, and $\mu_A(x_i)$ is the membership function of element x_i in the universe of discourse when the support set is a finite set:

$$X = \{x_1, x_2, x_3, x_4, \ldots, x_n\}. \tag{6}$$

Figure 4 shows how the predicate functions from the composition of the fuzzy set. These predicate functions have a special shape, height, and line style to represent their membership function; in general, triangles, and trapezoids are the most commonly used shapes, as they are simpler in terms of calculation.

Complexity of service order (c)	Assigned Operation time (T)
	Quantity of the item (Q)

	S				
	F	**RF**	**N**	**RM**	**M**
S	X	X	NC	SlI	SlI
RsI	X	X	NC	SlI	SlI
N	X	X	NC	SlI	SiI
RC	X	SlI	SlI	SiI	SuI
C	SlI	SlI	SiI	SuI	SuI

	RS				
	F	**RF**	**N**	**RM**	**M**
S	X	X	NC	NC	SlI
RsI	X	X	NC	SlI	SlI
N	X	X	NC	SlI	SiI
RC	X	X	NC	SlI	SiI
C	X	X	SlI	SiI	SuI

	N				
	F	**RF**	**N**	**RM**	**M**
S	SiD	SlD	SlD	NC	NC
RsI	SlD	NC	NC	NC	SlI
N	NC	NC	NC	NC	SlI
RC	NC	NC	NC	SlI	SlI
C	NC	NC	SlI	SlI	SiI

	RL				
	F	**RF**	**N**	**RM**	**M**
S	SuD	SuD	SiD	X	X
RsI	SuD	SiD	SlD	X	X
N	SiD	SlD	NC	X	X
RC	SiD	SlD	NC	X	X
C	SlD	SlD	NC	X	X

	L				
	F	**RF**	**N**	**RM**	**M**
S	SuD	SuD	SiD	SlD	X
RsI	SuD	SiD	SlD	X	X
N	SuD	SiI	SlD	X	X
RC	SiD	SlD	SlD	X	X
C	SiD	SlD	NC	X	X

Figure 5. Example of fuzzy rule blocks in SRM.

The input fuzzy set comprises several membership values from different fuzzy inputs. The expression of membership value is:

$$\mu_a = \mu_k(x)|_{x=a} = b, \tag{7}$$

where a and b are real numbers, representing crisp input data and membership value respectively, and $\mu_k(x)$ is the fuzzy set. These values are the intersection of the two equations represented by the crisp input data and the function of the predicate.

3.2.2 *Fuzzy inference engine*

The fuzzy inference engine is the second stage of the SRM. The input fuzzy set is converted into an output fuzzy set through an inference process that comprises four steps: rule block formation, rule composition, rule firing, and aggregation.

3.2.3 *Rule-block formation*

The rule block consists of a number of fuzzy rules that are interrelated and normally operate according to certain set criteria. The number of rules is determined by the complexity of the associated fuzzy system. A fuzzy rule is composed of two parts, namely an IF part and a THEN part. In this research, a number of rules are established for suggesting actions to support SRM. Rules can be displayed in a table format that can be easily searched. Figure 5 shows the example of fuzzy-rule block tables of PnP operation in SRM, including three input dimensions.

3.2.4 *Rule composition*

Rule composition is the process for calculating the membership values in the finalised rule input. The input fuzzy set is related to a specific predicate function, which has one membership value, by adding the crisp input data. In the SRM, there are three crisp inputs in each rule to cope with three different input fuzzy sets. As a result, three membership values are calculated. If a given fuzzy rule has multiple antecedents, the fuzzy operators will be used to obtain a single number that represents the result of the antecedent evaluation. This number is then applied to the consequent membership function.

To evaluate the disjunction of the rule antecedents, we use the OR fuzzy operation.

$$\mu_{A\cup B}(x) = \max[\mu_A(x), \mu_B(x)]. \tag{8}$$

In order to evaluate the conjunction of the rule antecedents, we use the AND fuzzy operation.

$$\mu_{A\cap B}(x) = \min[\mu_A(x), \mu_B(x)]. \tag{9}$$

Moreover, the suitable fuzzy rules are selected and activated by a screening process. The activated rules are fired and picked out for further analysis. There are many rules in the fuzzy system, but only some of the rules are fired, subject to the operating conditions.

3.2.5 *Aggregation*

Aggregation is the process of unifying all the outputs of rules. The membership functions of all rule consequents previously clipped or scaled are taken and combined into a single fuzzy set. Hence, the input of the aggregation process is the list of clipped or scaled consequent membership functions, and the output is one fuzzy set for each output variable (Negnevitsky 2005).

3.2.6 *Defuzzification*

Defuzzification, the last step in SRM, is a decoding operation that produces a single crisp value as an output. In this study, the centre-of-area (COA) method is adopted in the defuzzification process. Theoretically, the COA is calculated over a continuum of points in the aggregated output membership function, but in practice, a reasonable estimate can be obtained by calculating it over a sample of points, as shown in Equation (10) below (Leung *et al.* 2003, Lau *et al.* 2008):

$$\mathrm{COA} = \frac{\sum_{j=1}^{N} w_j C_j A_j}{\sum_{j=1}^{N} w_j A_j}, \tag{10}$$

where w, C, and A denote the weight, centre of gravity (COA), and area respectively.

4. Case study

A case study has been conducted in collaboration with Kennal (anonymous name), an SME 3PL company in the Pearl River Delta Region of China. There are 150 employees in the company, including 70 warehouse operators, four warehouse managers, five logistics coordinators, and three logistics engineers. Kennal provides outsourced logistics services to companies to help manage their supply chain. The service areas of Kennal include vendor-managed inventory, SKU management through kitting and assembly, centralised quality control, and retail compliance.

4.1 *PnP operation in Kennal*

Figure 6 illustrates a simple layout for the PnP procedure as used in Kennal. For example, a houseware-store customer makes an order to PnP 512 table lamps for the UK. The table lamp consists of six SKUs: the lamp stand, lamp cover glass, LED lighting, internal package, outer package, and regional user guide. The lamp stand and lamp shade are in different SKUs (different colours and different patterns, respectively). According to the customer orders (i.e. postponement), Kennal first picks all required SKUs from the storage area. During the PnP operation, the warehouse operators (with forklift) pick the required quantity of items and drop the pallets into the waiting area. The crew supervisor will setup a layout according to PnP procedures, design the sequence of the task, and allocate the crew to each operation/task. During the process, the crew supervisor is responsible for monitoring all procedures, checking the quality, and counting the final products. A crew member is responsible for packing all finished products into the carton, followed by sealing the carton and affixing shipping label.

The PnP process is similar to a simple production line, but with a more flexible layout. The crew supervisor can handle the operation effectively while the procedures are relatively simple, as shown in Figure 6. However, if the supervisor underestimates the complexity of the procedure or sets up the layout poorly, this can result in longer lead times

4.2 *Implementation of IPPS*

The IPPS implementation team in Kennal consists of four members: a logistics coordinator, a logistics information system engineer, a warehouse manager and a crew supervisor. The preparation time of this case-study testing is around two days, and the testing starts within the peak hours.

A prototype system is developed in accordance with the infrastructure of IPPS. The development team devised a prototype IPPS based on the infrastructural details and the design methodologies mentioned in Section 3. The main programming tool for the IPPS development was Visual Studio.Net 2003. The two main components, CBRM and

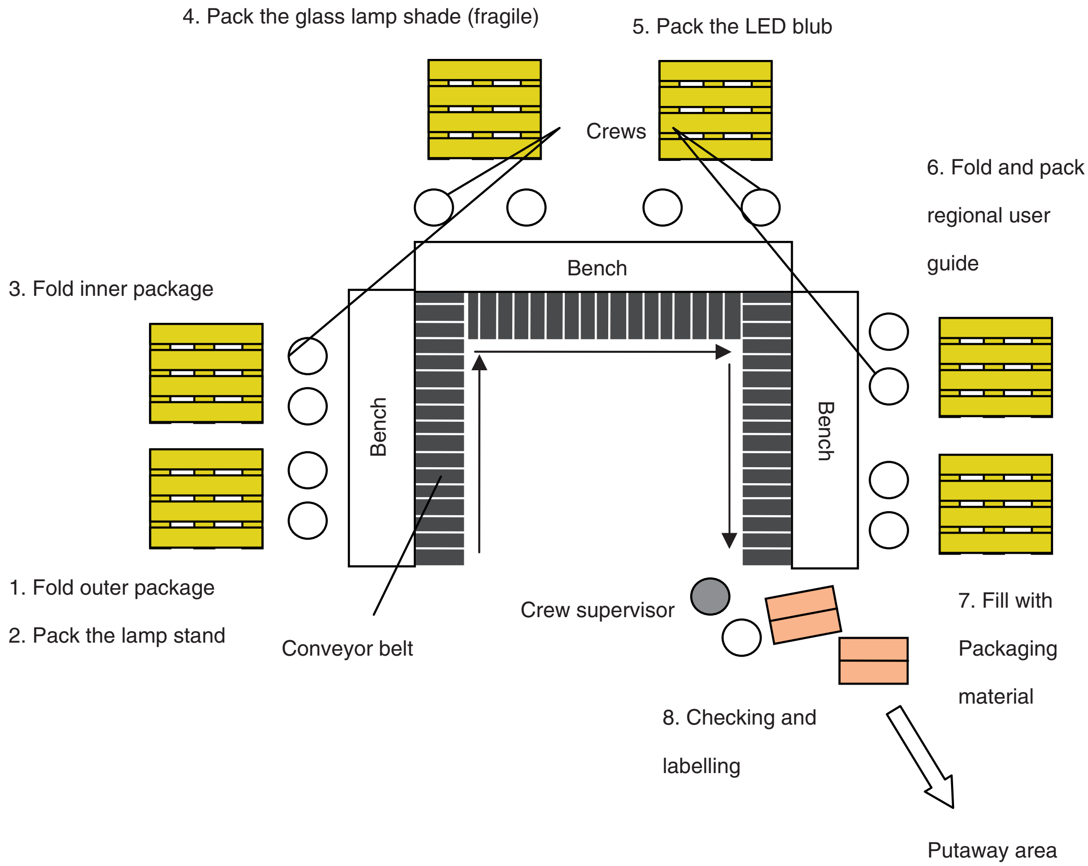

Figure 6. Example of a pick and pack operation.

SRM were developed in C#.Net language. The database server used in all repositories was Microsoft SQL Server 2000. The developed program was then tested to validate the feasibility of the concept using the Kennal case study. In CBRM, the case repository stores a number of cases of previous PnP service plans. Every case has a unique number that is assigned sequentially within the system. The flow for achieving a good-quality service plan starts with inputting the information and specifications of the customer's requests. The requests will be formulated into a format for the system to process. Then, the logistics coordinator will input the parameters of warehouses service requirements, which describe individual packaging activities and standard operation procedures. In SRM, the rules in the fuzzy tables are defined by warehouse-management experts (i.e. the warehouse manager, logistics coordinator, and crew supervisor). The updated information (such as finished quantity, remaining time, and updated complexity) will feed back to the SRM in a certain period of time (the initial setting is a quarter of total time). Figure 7 summarises the two stages process of IPPS.

4.3 *Stage 1: retrieval of the suitable operation plan*

First, when retrieving cases from the CBRM, the information is entered, such as product type, service type, and required specification, to filter out any irrelevant cases. A similarity analysis is then used to select the cases of close similarity, based on the nearest-neighbour retrieval function.

Thus, the CBRM retrieves the solution that is most similar to the target case, and the crew supervisor can make several adjustments to the solution parameters to assist the case adaptation process. Figure 8 shows the interface for the IPPS prototype. The operations involved in the logistics plans are shown on the left-hand side of the interface (the right-hand side of the frame illustrates the workflow of packaging operations). From the interface, the crew supervisor can view the details of the workflow and customise the parameters of each operation. With the support of IPPS, a logistics plan for solving complicated PnP problems is provided. The solution involves a customised

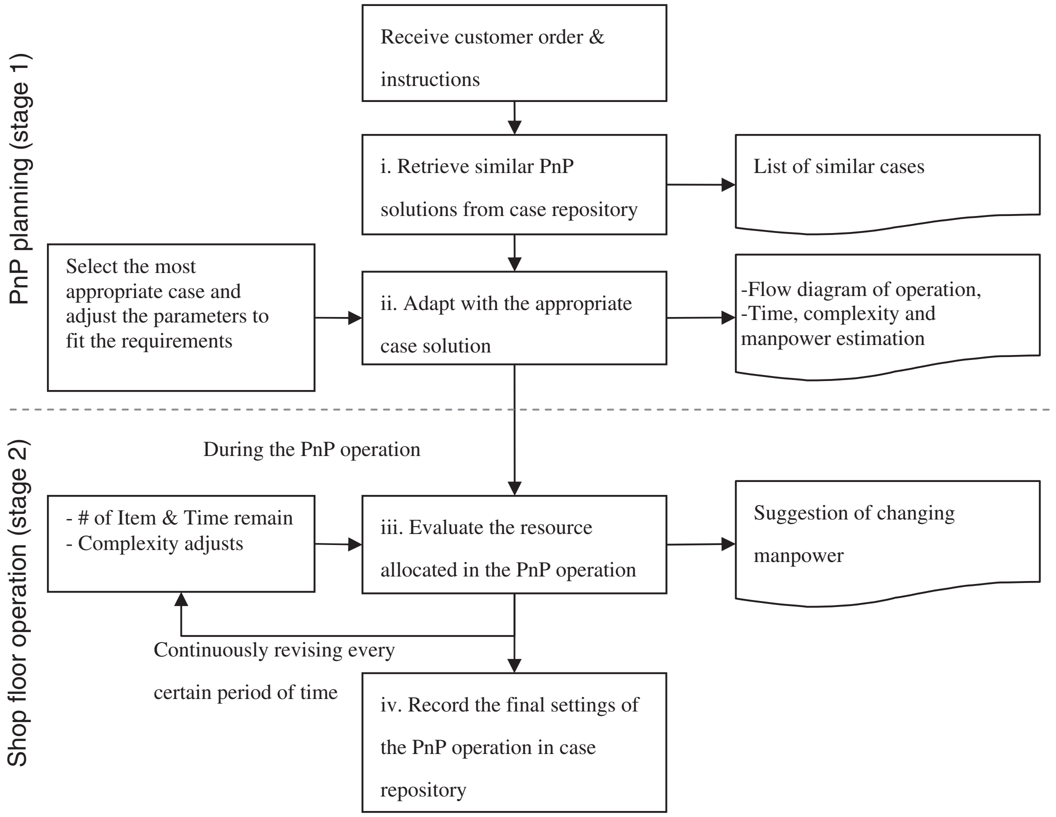

Figure 7. Flow diagram of IPPS.

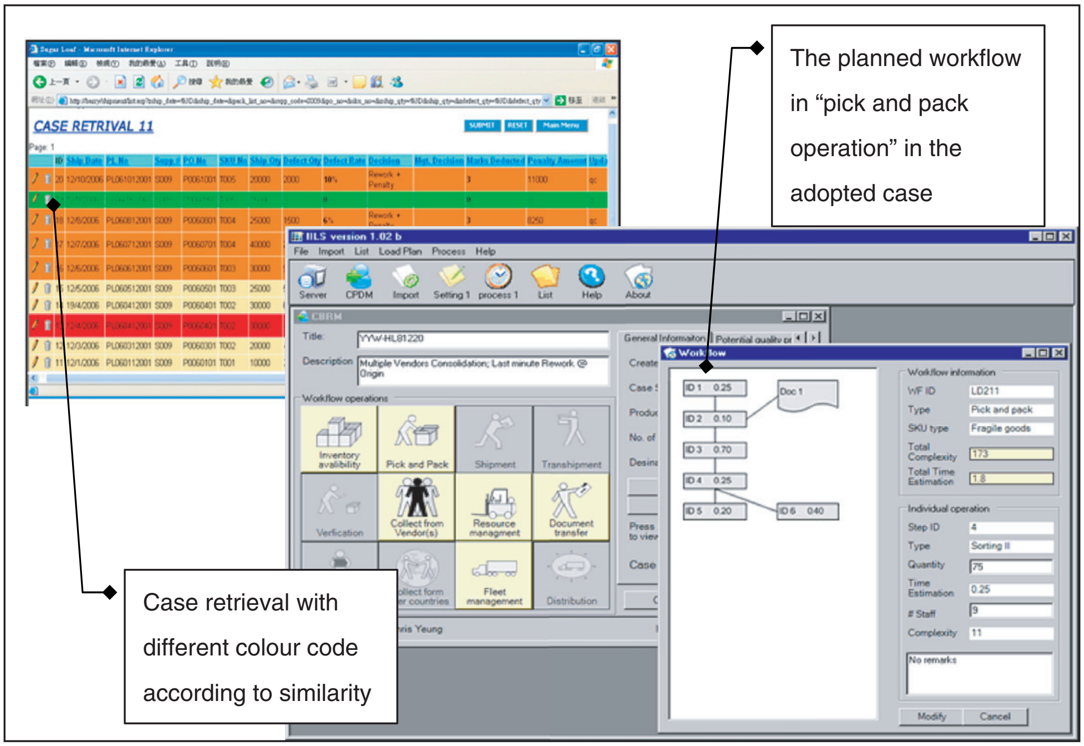

Figure 8. Screenshot of the IPPS prototype.

Table 3. Linguistic variables of input and output fuzzy sets.

	Fuzzy set	Linguistic variables
Input	Complexity level of service order (C)	C = {Simple (S), Rather Simple (RS), Normal (N), Rather Complex (RC), Complex (C)}
	Assigned operation time in job (T)	T = {Short (S), Rather Short (RS), Normal (N), Rather Long (RL), Long (L)}
	Quantity of item in the service order (Q)	Q = {Few (F), Rather Few (RW), Normal (N), Rather More (RM), More (M)}
Output	Labour resource change (H)	H = {Substantially Decrease (SuD), Significantly Decrease (SiD), Slightly Decrease (SlD), No Change (NC), Slightly Increase (SlI), Significantly Increase (SiI), Substantially Increase (SuI)}

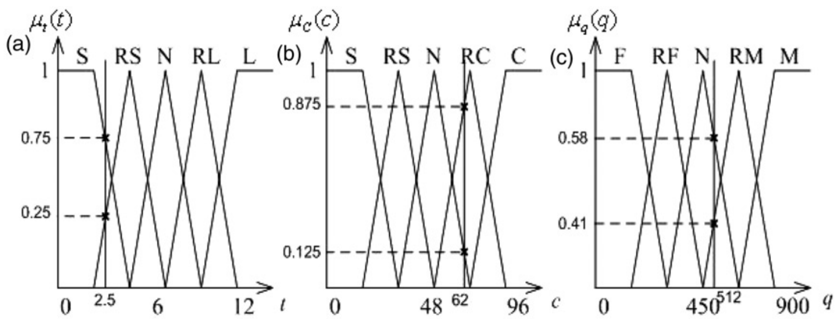

Figure 9. Membership value of $\mu_t(2.5)$, $\mu_c(62)$ and $\mu_t(512)$.

workflow. Standard operation procedures and suggestions for adjustment of resources used for the service order are provided. As shown in Figure 8, there are seven operational procedures involved in the PnP service. Estimations of the processing time, crew member allocated, and complexity of the workflow are calculated through the adaptive process.

4.4 *Stage 2: fine tuning of the qualified logistics plan by the fuzzy inference engine*

In this case, the qualified solutions are passed to SRM for further adjustment of the human resources allocated to each job. Three input parameters and one output information are chosen as the input and output. The input and output fuzzy sets associated with different linguistic variables are listed in Table 3.

Every qualified solution will undergo fine-tuning procedures. The three inputs to the SRM are: *complexity level* of service order, assigned *operation time* in jobs, and *quantity* of item in the order, which in this case are 62, 2.5 h, and 512 pieces, respectively. The complexity level is the order complexity index calculated in the CBRM stage and is calculated using Equation (4). The crisp values intersects with the predicates functions as illustrated in Figure 9. The resultant membership values obtained are listed in Table 4.

The highlighted cells in the rule table illustrated in Figure 5 are the rules that have been fired. In total, there are eight rules fired. An example of a fired rule is: IF average operation time IS *small* AND complexity of the service order IS *rather complex* AND quantity of item IS *normal*, THEN the labour resource change IS *slightly increased*. Eight composite results are calculated and shown in Table 5. The implication results are generated by the AND fuzzy operator as shown in Figure 10(a)–(h). The aggregation results are generated by the OR fuzzy operator as shown in Figure 10(i).

The last step in SRM is defuzzifying the output fuzzy set into crisp values. The method of COA is adopted in this case, owing to its simplicity of use. The calculations of each polygon are shown in Table 6. The defuzzification result

Table 4. Resultant membership values.

Fuzzy set	Resultant membership values
Complexity level of service order (C), i.e. Figure 9(a)	$\mu_{62}(c) = \mu_{RC}(c)\|_{t=62} = 0.875 \quad \mu_{62}(c) = \mu_{N}(c)\|_{t=62} = 0.125$
Assigned operation time in job (T), i.e. Figure 9(b)	$\mu_{2.5}(t) = \mu_{S}(t)\|_{t=2.5} = 0.75 \quad \mu_{2.5}(t) = \mu_{RS}(t)\|_{t=2.5} = 0.25$
Quantity of item in the service order (Q), i.e. Figure 9(c)	$\mu_{512}(q) = \mu_{N}(q)\|_{t=512} = 0.58 \quad \mu_{512}(q) = \mu_{RM}(q)\|_{t=512} = 0.41$

Table 5. Composition results in SRM.

Rule	Composition result (operation time) (complexity) (quantity) = (labour resource change)	Corresponding figure
Rule 1	$(0.75 \wedge 0.125 \wedge 0.58) = 0.125$	11(a)
Rule 2	$(0.75 \wedge 0.125 \wedge 0.41) = 0.125$	11(b)
Rule 3	$(0.75 \wedge 0.875 \wedge 0.58) = 0.58$	11(c)
Rule 4	$(0.75 \wedge 0.875 \wedge 0.41) = 0.41$	11(d)
Rule 5	$(0.25 \wedge 0.125 \wedge 0.58) = 0.125$	11(e)
Rule 6	$(0.25 \wedge 0.125 \wedge 0.41) = 0.125$	11(f)
Rule 7	$(0.25 \wedge 0.875 \wedge 0.58) = 0.25$	11(g)
Rule 8	$(0.25 \wedge 0.825 \wedge 0.41) = 0.25$	11(h)

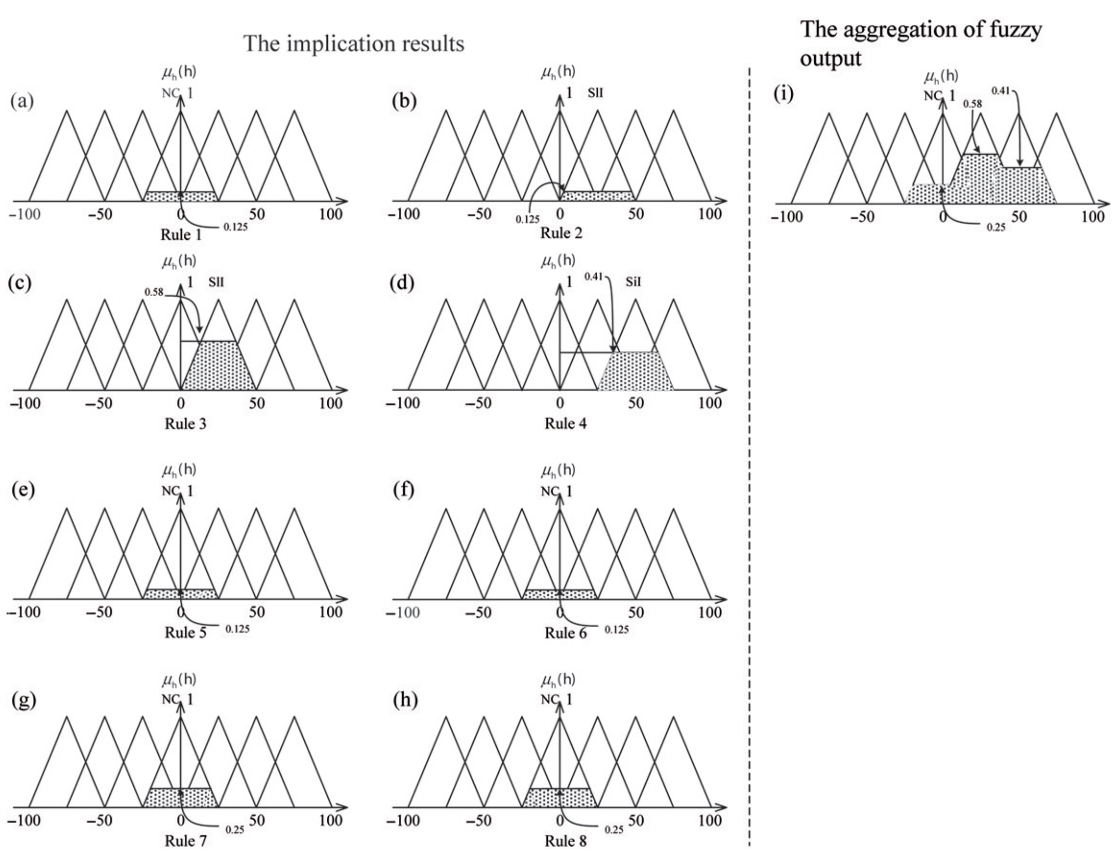

Figure 10. Implication and aggregation results.

Table 6. Data of defuzzification.

Rule	Area (A)	COG	Weight (w)	w * C * A	w *A
1	5.86	0	1	0	5.86
2	5.86	25	1	146.5	5.86
3	20.59	25	1	514.75	20.59
4	16.30	50	1	815	16.3
5	5.86	0	1	0	5.86
6	5.86	25	1	146.5	5.86
7	10.94	0	1	0	10.94
8	10.94	25	1	273.5	10.94

is found by applying Equation (10), for example:

$$\frac{\sum_{j=1}^{N} w_j C_j A_j}{\sum_{j=1}^{N} w_j A_j} = \frac{1896.25}{82.21} = 23.07.$$

After the defuzzification process, the COA is 23.07%. That means the crew supervisor should assign 23% more crew members to be involved in this PnP operation.

Moreover, the solution is being adjusted continuously during the operation. Thus, the handheld reader of the last checking point of the process will transfer up-to-date operational information (i.e. the output rate) to the IPPS during every 20 min (the updating time is adjustable). In addition, the crew supervisor is able to adjust the complexity index of the operation subject to crew performance. The IPPS is then able to automatically capture the percentage of order completeness and calculate the time left of operation in every certain period of time and alert the crew supervisor to change the number of crew members in their team.

4.5 *Discussions*

During prototype testing of IPPS, two senior managers of Kennel were invited to observe the testing process and to further evaluate the IPPS system. The two managers did not have prior knowledge about the IPPS development (i.e. not involved in the IPPS development) so that they could give an independent evaluation of IPPS. After the test, a focus group was formed, comprising the two senior managers, the crew supervisor and the logistics coordinator (the latter two members were involved in the test and implementation of IPPS). The focus group found the results encouraging and believed that the IPPS system could effectively support the PnP operation. One of the senior managers commented that the IPPS would enable the company to maintain a consistent PnP service level. He also pointed out that the typical feature of knowledge retention and reuse could be made more effective based on their previous knowledge and experience. More importantly, all the PnP testing operations were successfully finished within the schedule. He claimed, 'The solution planning support of IPPS can improve the planning accuracy which is an important issue in a seamless logistics flow'. However, the 'control group' test is not conducted for comparing the performance between the traditional and IPPS approach because different PnP orders always have different quantities and PnP requirements. Therefore, it is hard to form a control group and run the traditional approach with the same size of order and the same customer requirements.

In addition to the support from the managers in the focus group, the crew supervisor was also impressed by the real-time feature of adjusting labour resources during the PnP operation. He pointed out that one of the major benefits of using IPPS is being able to continuously evaluate the PnP performance in every certain period of time. Thus, he could monitor the process of PnP service effectively and accurately. The IPPS would alert him to adjust the labour resource if it estimated that the completion of PnP operation might be behind the schedule. For example, the case study in Section 4.4 illustrates that the IPPS advises the team supervisor to add an extra 23% of manpower to catch up with the schedule.

Another manager further claimed that '... our pick and pack operation always "lagged behind the schedule" or "finished earlier than expected". ... To prevent the disruption of the logistics flow, our current approach prefers to assign more staff and have more buffering times for the operation'. However, given the tough economic times, effort to reduce operation costs inevitable leads to less staff being employed for warehouse operation. One manager subsequently commented that '. . . the suggestion of manpower reduction in IPPS can be useful while there are multiple pick and pack operations processing simultaneously'. Therefore, redundant resource can be reallocated to another PnP lines if needed.

In addition, the logistics coordinator stated that the effectiveness of the labour resource adjustment mainly depended on the range as defined in the fuzzy set. He recommended that the range of each fuzzy set should be revised by the crew supervisor after the completion of each PnP order, with the new fuzzy set retained in the case repository. IPPS also has limitations in that the labour-resource adjustment process would ignore the effect of the crew members' learning curve during the operation. Moreover, the "new added labour" may work less efficiently than the original crew members do. A more sophisticated adjustment could be made if the factor of labour learning curve is also included in the adjustment mechanism in the SRM.

In sum, the IPPS can benefit 3PL as follows:

(1) Continual improvements in the PnP operation. By using IPPS, the logistics coordinator and crew supervisor are able to continually update and modify the PnP operations in real time to fit various working situations and customer requirements. The new solution is retrieved by comparing the previous and similar situation that they had already solved. Then, the SRM can continuously adjust the labour resource to improve the performance on the 'shop floor'. Thus, the IPPS provides a continuous improvement in PnP operation by retrieving an effective solution, and also provides an adaptation capability to respond to different types of PnP operations in a real time manner. The 'incremental knowledge' in PnP planning and the 'adaptation ability' of shop-floor operations were seen by the managers as essential for continual improvements in PnP operation.
(2) Real-time adjustment in labour-resources allocation. IPPS supports a fast, responsive adjustment in manpower allocation. The fuzzy control function in SRM provides suggestions for adjusting the allocation of labour resources to assigned jobs by considering the current warehouse situation. Moreover, the performance of PnP operations is evaluated periodically, and adjustment suggestions are immediately provided while IPPS predicts a longer lead time. Accordingly, the PnP operations can be completed within the schedule. Moreover, excessive labour resources in one task can be reallocated to other tasks that have insufficient resources. Hence, better labour-resource utilisation in the warehouse can be achieved. Also, as the labour resources have been allocated properly, the order can be completed within the schedule. Thus, the total costs owing to quality problems of unsatisfactory service can also be reduced.

The managers at Kennal suggested that IPPS can be adopted to improvements in other warehouse operations such as forklift allocation in order picking. The feedback features of IPPS can improve the on-site operation in a real-time manner, a potential avenue for futher research.

5. Conclusion

In this paper, a new approach IPPS has been proposed, providing high-quality, reliable, PnP solutions for 3PL. This infrastructural framework, supported by CBR and FL, is a decision-support system with special features to cope with complicated postponement activities. The major contribution of the proposed system is to enhance PnP operation by providing a proper solution plan, and to continuously improve the 'light manufacturing' performance in 3PL by refining labour resource allocation in the PnP operation. The feature of continual improvement can avoid the loss of knowledge and prevent the same mistakes being repeated in similar PnP problems. The PnP solution is being continuously refined during the shop-floor operation. The IPPS can make suitable real-time judgements to change labour resources during operations in order to complete the PnP service within the schedule.

Although encouraging results have been achieved, there are a number of aspects that need investigating further. First, the accuracy of real-time resource adjustment on the shop floor depends greatly on the expertise of the crew supervisor to define the fuzzy set values. Thus, an additional evaluation module may be needed to ensure the quality of defined fuzzy sets. Second, the real-time resource-adjustment process can have a more sophisticated judgement by considering the effect of the crew members' learning curve during the operation. Further research will also focus on testing the IPPS in other warehouse operations, such as order-picking operations. All these undertakings will provide a more comprehensive platform for managers to use this intelligent system as a useful decision-support tool for 3PL.

Acknowledgements

We would like to thank three anonymous reviewers for providing valuable comments to improve the quality of the manuscript.

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