Solving Complex Logistics Problems with Multi-Artificial Intelligent System

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Abstract: *The economy, which has become more information intensive, more global and more technologically dependent, is undergoing dramatic changes. The role of logistics is also becoming more and more important. In logistics, the objective of service providers is to fulfill all customers' demands while adapting to the dynamic changes of logistics networks so as to achieve a higher degree of customer satisfaction and therefore a higher return on investment. In order to provide high quality service, knowledge and information sharing among departments becomes a must in this fast changing market environment. In particular, artificial intelligence (AI) technologies have achieved significant attention for enhancing the agility of supply chain management, as well as logistics operations.*
In this research, a multi-artificial intelligence system, named Integrated Intelligent Logistics System (IILS) is proposed. The objective of IILS is to provide quality logistics solutions to achieve high levels of service performance in the logistics industry. The new feature of this agile intelligence system is characterized by the incorporation of intelligence modules through the capabilities of the case-based reasoning, multi-agent, fuzzy logic and artificial neural networks, achieving the optimization of the performance of organizations.
Keywords: Decision support system, logistics flow enhancement, integrated system

1. Introduction

In the economy, which has become more information intensive, more global and more technologically dependent, the role of logistics is becoming more and more important (Olavarrieta & Ellinger, 1997). In logistics, the objective of service providers is to fulfill all customers' demands while adapting to dynamic changes of logistics networks so as to achieve a high degree of customer satisfaction and therefore a higher return on investment. Customer satisfaction is a vital indicator which reflects customer expectations, actual logistics service performance and the gap between those two. As revealed from past research, not only post-purchase customer interactions and the customer's pre-purchase logistics service expectations can increase customer satisfaction, but also the ability to provide a high level of logistics service. Reliability begins to be taken for granted and becomes the price for admission to any market which deals in high value-added services. Quality of service is then the key element and synonymous with the customer's ability to choose from a wide array of logistics service providers which provide a close match to individual needs and desires. Customers are asking for outstanding logistics service in all dimensions, which, preferably, can be tailor-made to suit their constantly changing requirements.

It can be seen that the emphasis is now on adaptability to change in the business environment and a proactive way of approaching customer needs. Many logistics companies work very hard to produce services of a high standard. In order to do this, every process of the logistics operation must be effective and efficient. In fact, a high level of logistics service is not the responsibility of any one person or functional unit, but it is everyone's job. The areas responsible for improving performnce of a logistics work flow included warehouse receiving, inbound putaway processing, inventory tracking, transportation, cross-docking, return processing, shipping, picking, packaging, etc.

In order to facilitate the realization of providing high quality service, knowledge and information sharing among departments becomes a must in a fast changing market environment. The utilization of information technology is taking up momentum to meet this challenge. In particular, artificial intelligence (AI) technologies have achieved significant attention for achieving agility of logistics flow, which plays an important role in enhancing logistics service and quality.

The objective of this research is to develop the Integrated Intelligent Logistics System (IILS) in order to achieve high levels of service performance in the logistics industry. The rest of this paper is organized as follows: Section 1 is the introduction; supportive literature is presented in Section 2; The infrastructure of the proposed IILS is described in Section 3; The modules included in the framework on how to provide quality solutions for

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complex logistics problems are described in Sections 4 to 7; The procedures of system development and its findings of the implemented system are examined in Section 8.

2. Related studies

Exceeding customer expectations is vital for achieving success of a growing, quality organization and form surviving in the increasingly customer-oriented market (Ho et al., 2005). As business evolves to embrace agility, the supporting systems, tools and structure must also evolve. The need to effectively integrate decision-making tasks, such as interactive access to data and support for numerical and quantitative modeling techniques in semi-structured problems, together with the knowledge representation tasks and inference procedures that model an expert's thought process, has provoked recent research efforts to integrate decision support systems with knowledge-based expert systems (Nikolopoulos & Assimakopoulos, 2003).

Supply chain researchers have applied various complementary approaches so as to resolve problems in collaboration, including optimization-based, multi-agent-based, and simulation-based. Each approach has unique strengths, but only identifies optimal solutions for given situation subject to specific assumptions. These approaches are generally applicable to inventory management, logistics optimization, and vehicle scheduling (Kwon et al., 2003).

Expert systems, can be used in process monitoring, quality control and simulation. Paladini (2000) pointed out that AI can be used for organizing and structuring a reliable, fast and practical procedure for executing quality evaluation, cost effectively.

2.1. Case-based reasoning

Case-based reasoning (CBR) is one of the AI approaches applied in decision support and problem diagnosis. New engineering problems are solved by referring to similar cases that have occurred in the past which can be retrieved and adapted to suit the new case. CBR is liked by many industries, as they can relate better to case examples rather than drawing conclusions separated from their context. Huin *et al.* developed a knowledge-based tool for planning enterprise resources. CBR technique is employed to formulate potential solutions to derive the planning model from previous similar cases by assessing complex trade-offs among various qualitative factors, and by using past experience (Huin et al., 2003). Another CBR system for supporting the workflow modeling and design was proposed by Madhusudan. A case representation for workflow schemas and objects that combines both declarative and procedural representations was developed. The retrieval algorithm is based on graph-based queries. A domain independent AI planning technique is used to facilitate composition of cases into a workflow (Madhusudan et al., 2004).

2.2. Multi-agent system

A number of related studies about the agent-based model and software agents have been conducted in recent years. They have achieved to a limited extent a number of human-like activities. The application is normally confined to "watchdog" services for alerting users when unusual events surface (Ferber, 1999; Ho et al., 2005; Lim & Xhang, 2007). A multi-agent system (MAS) was proposed for supporting the planning of transshipments and storage allocation via a seaport in Gehring and Fischer (Gehring & Fischer, 2005). The MAS can support the distribution of the decision competencies by assigning a specific type of agent to problems of storage allocation and deployment scheduling. Ying and Dayong (2005) proposed the multi-agent framework for third party logistics, such as building up a virtual private logistics subsystem with a MAS for integrating logistics business processes of logistics companies and supply chain members. Furthermore, Karageorgos *et al.* suggested an agent-based and the holonic paradigm approach to support non-trivial integration of manufacturing and logistics service planning. In such approaches, negotiation is used to reduce the number of planning and scheduling alternatives via negotiation-based contracts (Karageorgosa et al., 2003).

2.3. Fuzzy logic

Traditional optimization methods of operations research, including multi-criteria optimization methods, strive to find a single "best" solution to problems. However, in less-structured problems with the presence of complexities and uncertainty, the notion of optimality may be fuzzy at best. With these problems, there is often some degree of uncertainty about the desired state, and the objective is not clear (Toivonen et al., 2006). In such a situation, fuzzy logic (FL) is the appropriate technology to substitute for the human expert, when a choice needs to be made. FL is applied in various areas in process control and decision support. Ahmed *et al.* proposed a FL based thermostat programming scheme for a central air-conditioning system. A central air-conditioning system is corrected taking into account the temperature and humidity data. The intricate relationship between temperature and the humidity of the space is cooled through a set of fuzzy rules (Ahmed et.al, 2007). Moreover, a fuzzy logic-based inventory control model is proposed by Samanta and Al-Araimi (2001). It maintains the inventory at a desired level in spite of fluctuations in the demand, taking into account the dynamics of the production system. The concept of fuzzy set theory had been applied to inventory control models considering the fuzziness of inputs and the dynamics of the systems.

2.4. Artificial neural networks

Artificial neural networks (ANNs) learn by example in a way that corresponds to the learning process of the human brain. ANNS can be divided into two groups: (a) supervised learning ANNs and (b) unsupervised learning

ANNs. Supervised ANNs learn under the supervision of a 'teacher', who knows what the right output should be and steers the learning process in this direction. Unsupervised ANNs learn only using input data during the training process and ANNs do not have any prior knowledge of the desired outcome. Therefore, the network forms a representation of the behaviour of the input data (Toivonen et al., 2006).

ANNs can be utilized in a wide variety of areas, such as manufacturing and supply chain management. Kim *et al.* (2003) proposed ANNs model to predict process parameters on top-bead width in the robotic gas metal arc welding process. The model is capable of making top-bead width predictions of the experimental values with reasonable accuracy. Ho et al. (2005) proposed a quality enhancement system where ANNs are adopted to evaluate the feasibility of quality enhancement solutions in the slider fabrication industry. ANNs techniques are also applied in traffic forecasting. An object-oriented neural network model for predicting short-term traffic conditions is developed by Dia (2001). ANNs used for prediction consist of an input layer comprising speed and flow data from the upstream and downstream stations.

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2.5. Integrated intelligent systems

Intelligent systems are widely applied in different domains. They are capable of addressing applications efficiently. Each intelligent system has inherent strengths and limitations. The recent trend has been towards integrating the intelligent systems to solve problems of high complexity. This approach not only improves the strengths of individual AI techniques but also lessens their drawbacks (Sonar, 1999). An intelligent system integrated with ANNs and fuzzy logic has been proposed by Lee and Wong for decision making in foreign currency risk management (Lee & Wong, 2007). ANNs are employed to forecast foreign exchange rate movements. This is followed by intuitive reasoning of multi-period foreign currency returns using multi-value fuzzy logic. Kwon *et al*. developed a framework based on MAS and CBR to enhance collaboration and information sharing in the presence of high supply and demand uncertainties (Kwon et al., 2007). The integrated intelligent system has also become a new approach for quality enhancement in different industrial applications in recent years (Kim et al., 2003; Ho et al., 2005]. However, there are few research papers about the integrated intelligent system for improving quality service in the area of logistics. Logistics service solutions always involve combinations of complex logistics operations which mainly depend on the decisions of experienced logistics engineers. It is a challenge for logistics engineers to provide quality logistics solution planning without the support of an integrated intelligence system. In this research, an integrated intelligent logistics system (IILS) is proposed. This is an intelligent system integrated with various artificial intelligence techniques of CBR, MAS, FL and ANNs.

3. Infrastructure of IILS

The infrastructure and data diagram of the proposed IILS are shown in Figures 1a and Figures 1b respectively. Basically, the IILS consists of four major modules, namely, distributed problem solving module (DPSM), conflicting parameter determination module (CPDM), solution refining module (SRM) and solutions unifying module (SUM).

The distributed problem solving module (DPSM) is a module responsible for providing a logistics solution by using distributed problem solving techniques. It consists of two sub-modules (i) potential quality problem identification module (PQPIM) and (ii) distributed solution agents module (DSAM). The principle of PQPIM is that it adopts the CBR technology to identify the possible quality problems in the logistics workflow and divide them into several sub-problems based on different classes of the potential problems, which relies on the previous experience in similar cases. This module assigns the tasks to deduce the potential problems (i.e. to retrieve the most similar cases in the case base). These problems are divided into several sub-problems which are based on the solution provided in the most similar case. Then, all sub-problems are passed to the appropriate agents in the DSAM. DSAM contains a multi-agent system which implements blackboard communication architecture. Each of the agents inside this module is able to act
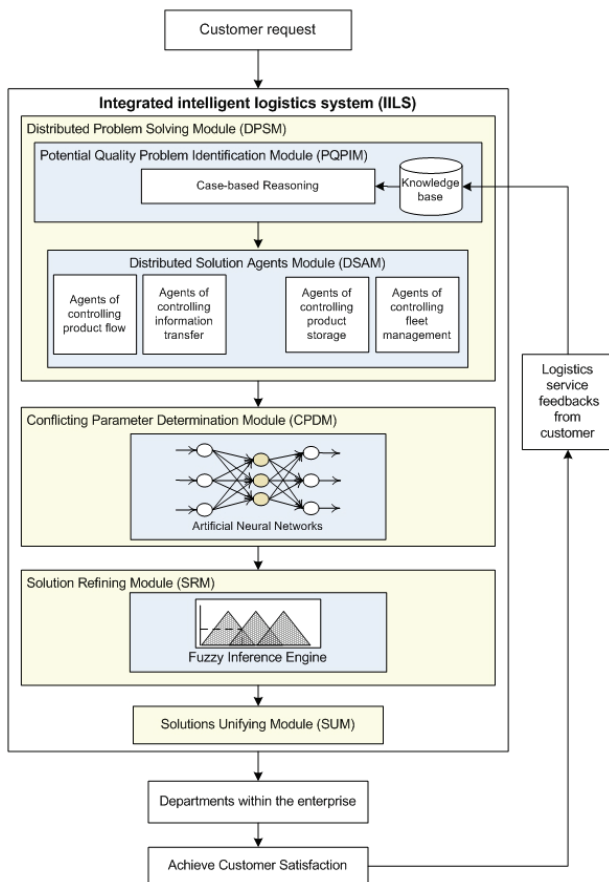
Fig. 1. Infrastructure of IILS.

autonomously, cooperatively and effectively to provide logistics solution with high quality and reliability. In distributed blackboard communication architecture, data are shared within the agent community via the public blackboard space. The blackboard is a place where agents post requests for help and experts answer the requests, so that agents do not need to interact with each other directly. The interactions among agents and blackboards are typed in a knowledge and query manipulation language (KQML). Messages for exchanging information are independent of content syntax and ontology.

CPDM is a module to guarantee that the quality of solutions generated by DSAM is up to standard. Since distributed problem-solving is applied in DSAM, local solutions generated are not considered in a global manner. That means the local solutions co-exist with conflicting parameters which may cause discrepancies and dynamic problems in the logistics workflow. Therefore, CPDM is developed to determine the existence of conflicting parameters in the proposed logistics solution. ANNs technology is embedded into CPDM for identifying conflicting parameters. Also, Multilayer perceptron (MLP) regression with a back-propagation algorithm is applied in this module.

SRM is used to refine the solution which contains conflicting parameters determined in CPDM. SRM adopts the fuzzy logic for adjusting some parameters to eliminate the conflicts among local solutions. Those

parameters are the system input values and therefore input membership function values can be obtained through fuzzification. Then, 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 using a chosen defuzzification method. Finally, another module, named SUM, will unify all of the solutions developed from different agents and distribute them to the relevant departments within the enterprise.

Although a logistics feedback system is not included in this framework, it is a channel for customers to give feedback and comments on the service to logistics service providers. Customers can score the logistics solutions and complain about these solutions. The most obvious function is to help uncover recurring service problems which are not stored in the knowledge base. The new service problem will then be formulated to a new case which will be indexed and repositioned into the knowledge base.

This infrastructure makes better use of distributed problem-solving features, with the collective effort of multiple problem solvers to combine their knowledge, information and capabilities in order to figure out solutions to quality problems, each of which could not be solved alone.

4. Distributed problem solving module (DPSM)

For achieving a high level of logistics service, performance failures such as late delivery and product unavailability are not allowed in logistics operations. In order to guarantee high performance in service, authorities in various areas need to make appropriate decisions in the domains for which they are responsible. Obviously, delegating responsibility for making quality decisions to different departments plays an important role in this module.

DPSM consists of two sub-modules, potential quality problem identification module (PQPIM) and distributed solution agents module (DSAM). CBR and MAS are adopted in PQPIM and DSAM respectively. The methodology employed in DPSM is the division of all the quality problem into a series of sub-problems related to specified areas. The sub-problems are assigned to the associated agents for searching for solutions. Client requirements are first input into the sub-module, PQPIM to identify which logistics operations need to be processed and the potential quality problems that exist in these operations. Each of the agents in the DSAM performs not only problem-solving in a distributed manner, but also problem-solving locally to arrive at a solution to its own sub-problem. The local solutions are filtered and then combined to arrive at a set of unified solutions for the original total problem (Oates et al., 1997). The purpose of this approach is to identify the potential failures which may occur in any step of a logistics operation. Independently, each mistake seems negligible;

however collectively, mistakes can be a major barrier to achieving world-class quality standards (Hinckley, 2001).

4.1. Potential quality problem identification module (PQPIM)

Case-based reasoning (CBR) is a popular problem-solving methodology that solves a new problem by retrieving previous, similar situations. The information will be reused and the knowledge from the previous case will be adopted in the current situation. A case repository of a CBR system stores past cases of the application domain. Each case in the case repository consists of two parts: the problem description part and the solution part. There is a set of attributes critical to the domain which is used to represent the former part of a case for the case matching process (Tsai & Chiu, 2007).

In this research, CBR is used as a new approach for logistics engineering teams to identify the potential quality problems of logistics service by matching the description of a given situation with the solutions of similar problems which occurred in the past. It provides a systematic procedure for representing the relationship between the responsibilities of departments, such as warehouse department, trucking department and shipping department within the company, and quality level of logistics service. Then, a set of potential problems is suggested and the new case based on the solution parts from similar past cases is generated. Generally, CBR has been formalized as a four-step process: (i) retrieving similar past cases from the case-base, (ii) reusing solutions from similar past cases to infer a proper solution to the current problem, and reusing the similar cases, and (iii) revising the proposed solution if necessary, and (iv) retaining the new solution by incorporating it into the existing case-base for future problem-solving (Kolodner, 1993). Figure 2 shows the structure of CBR used in this module.

The case base of PQPIM contains all of the previous customers' records with the quality problems related to service and the difficulties faced in different areas. Before providing services, the query is entered by the logistics consultants who assign values to the attributes attached to objects: input, output, and other characteristics. The query consists of the customer requests which are some elements of customer service policy. The policy is defined by the logistics manager and it normally depend on
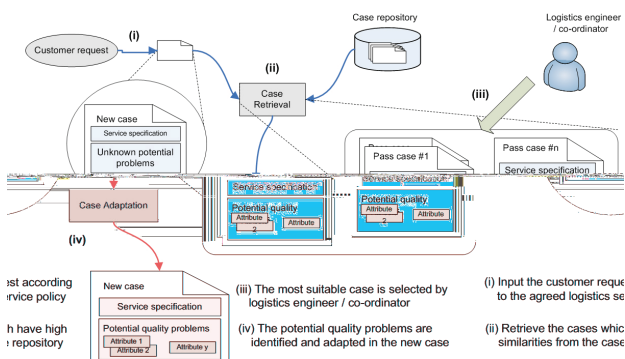
customer needs, definition of service standard, performance measurements and report frequency. The solution part of the adapted case is the list of the overview of quality problems which are broken down into several sub-problems such as insufficient storage area, poorly planned production flow, and fleet scheduling disorder. Subsequently, potential problems that have been identified are assigned to agents responsible for solving the problems using the multi-agent system in DSAM.

The tactics employed in this module use the nearest neighbour technique as the retrieval algorithm. By comparing and weighting the attributes, the similarities between the target case and the retrieval case in the case repositories can be acquired. The measure of similarities is given by (Kolodner, 1993):

$$\frac{\sum_{i=1}^{n} w_i \times sim\left(f_i^I, f_i^R\right)}{\sum_{i=1}^{n} w_i} \tag{1}$$

where w_i is the weighting factor of feature I, sim is the similarity function, and f_i^I and f_i^R are the values for features f_i in the input and retrieved cases, respectively.

4.2. Distributed solution agents module (DSAM)

Potential problems determined in the PQPIM will be distributed to agents and then these problems are treated as tasks in the DSAM. Task distribution involves the definition of the organizational mechanism through which agents can combine their skills to perform collective work (Ferber, 1999). Several parameters which need be taken account for the task distribution are: (a) agents' cognitive capacities, (b) their capacities for commitment, (c) skills of the individuals concerns, (d) nature of each task, (e) efficiency of each task, (f) cost of sending a message, and (g) social structure within which agents move. Task requiring more resources, work or expertise are broken down into several sub-tasks. Then, the various agents are allocated to finish those tasks. These two operations are clearly related and defined, as the breakdown often depends on the skills of the agents. This subsequently makes the distribution easier.

All the agents in the DSAM have their own expertise and intervene at different stages. All applications are covered by distributing the responsibility for solving the problem. It is assumed that it is possible to carry out a complex task by calling upon an assembly of specialists to work with complementary skills. The DSAM first decomposes the potential problems which affect logistics service performance into a number of individual sub-problems that are subsequently assigned to various intelligent agents. However, in the actual dispersed logistics network operating on a global basis, there are large numbers of intelligent agents involved. Also, more than one intelligent agent may fit the criteria to undertake a certain specific task in some cases. In this case, it is important that certain mechanisms are adopted to decide

Fig. 2. Data Flow Diagram of CBR in PQPIM

which agent is selected in order to minimize the overheads for carrying out the task.

In order to provide appropriate solutions for solving the problems in service, PDM developed, in this research, several agents. They are: resource management agent (RMA), cross docking agent (CDA), order agent (OA), item-location assignment agent (ILAA), task interleaving agent (TIA), pick and pack agent (PPA), shipping agent (SHA), truck scheduling agent (TSA), transshipment agent (TSHA), vehicle routing agent (VRA), custom documentary agent (CUDA), import/export clearance agent (IECA).

The agents mentioned above are classified into four categories:

1. *Control of product flow:* It is a major factor for improving the performance of a high quality logistics service. It aims at optimizing the time and cost of movement of products in logistics working process. Agents in this class provide a solution of movement of large quantities of raw materials, component parts, and finished goods through the warehouse in a fast, efficient and orderly manner.

2. *Fleet management:* It is always a critical factor in the delivery issue. A better approach to controlling the arrangement of docking and fleet improves the time accuracy and optimizes the cost. Within this approach, basic elements of the transportation network, such as truck, destinations, route and incoming orders are assigned to appropriate agents.

3. *Control of storage:* It involves assigning locations of the products for matching different kind of picking processes. It also involves utilizing the storage space of the rack, providing supporting information of layout design of the putaway area, and optimizing the volume of the items up to carton level and pallet level.

4. *Control of information flow:* It plays an important role in importation clearance and documentation exchange among clients, logistics providers and customs officials, coupled with the provison of timely, accurate information about the products being stored It also provides effective logistics service communication which is the goal of this class of agent.

Distributed blackboard communication architecture is implemented in this DSAM. In this architecture, agents do not need to directly interact with each other. The information is available in a common information space and there are no direct communications among agents. The blackboard is a place where agents post requests for help and those who are knowledgeable provide answers to the requests (Ferber, 1999; Jiang et al., 2004; Parrott et al., 2003). For instance, CDA posts a request on a blackboard about the time slot and availability of a staging area for cross-docking operations. TSA and RMA read the "call-for-help" post on the blackboard, and then they reply to the blackboard saying if they can manage it
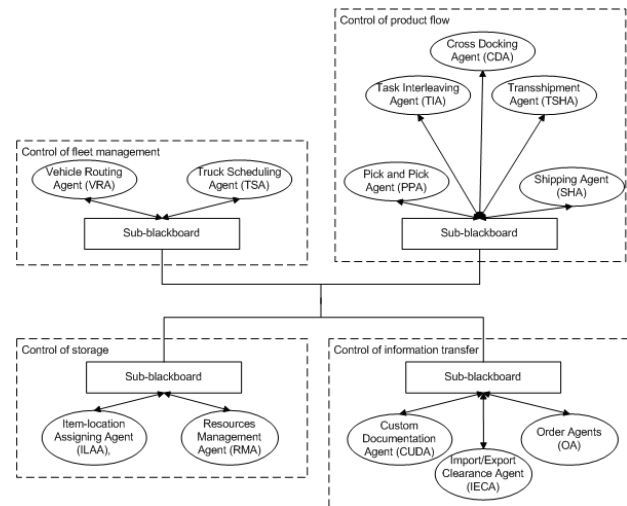

Fig. 3. Distributed Blackboard Architecture in DSAM.

or not. After the solution is worked out, an acknowledgement will be posted on the blackboard.

Some sub-blackboards are set in the system where each sub-blackboard is used for the communication of some particular agents. The agents in DSAM surrender their communication autonomy to the sub-blackboard which takes full responsibility for their needs. Figure 3 shows the implementation of the distributed blackboard communication architecture in DSAM in which there are four multi-agent sub-systems in their different classes of control. The agents in each sub-system are controlled by a sub-blackboard. The sub-blackboards communicate among themselves to express the needs of their respective agents.

Communication among agents is one of the important keys in MAS. Agents inside DSAM initiate the communication action by the Knowledge Query and Manipulation Language (KQML) which is the most widely used protocol for multi-agent systems. Basically, KQML offers a way to structure the messages in a layered architecture with the functionality of message communication. Between the layers are the primitives or performatives, with which agents can exchange meaningful messages. The KQML performatives are assertive and directive, used to perform actions like 'tell', 'evaluate', 'subscribe', or change agents' states, etc. With the KQML messages, agents can communicate with each other in a peer-to-peer manner (Wu, 2005).

5. Conflicting parameter determination module (CPDM)

In DSAM, distributed agents generate local solutions by using local parameters. They may not consider the solutions in a global manner. That means a local independent solution may be a high quality solution, but it may not be up-to-standard if the solutions are unified together. The quality of local solutions may correlatively affect each other. For example, task interleaving agent (TIA) generates a local solution which assigns a task to be inserted into the schedule of a lift truck operator. Then,

this operator performs an additional task to put away a pallet on his way before the next picking operation. This arrangement can greatly reduce travel times and thus increase the productivity. However, if the pick and pack agent (PPA) selects "wave picking" as the most suitable picking type in the operation according to the order profile, the interleaving task will be unable to be processed. As a result, the lift truck is not able to put away a pallet in this kind of picking type. The conflicting parameters among the local solutions may cause discrepancies with the reality and therefore should not exist in the DSAM.

This module is mainly to determine conflicting parameters of local solutions which are fed into ANNs. An ANN is used to evaluate these conflicting parameters of local solutions which are generated from the agents in a distributed manner. This evaluation process shows the relative strengths and weaknesses of the alternative parameters. A parameter will be identified as a conflicting parameter if it causes the output solutions to be infeasible or even unsatisfactory. The conflicting parameters will be shortlisted and passed to SIM for retuning the relative operation parameters.

In a neural network, each of neurons has an adjustable weight factor associated with it and a connection with all other neurons in the adjacent layer through the weighted connections (Kim et al., 2003).

Multilayer perception (MLP) regression with back-propagation is responsible for evaluating the existence of conflicting parameters which affect feasibility of solutions. Multilayer perceptions have been applied to solve some difficult and diverse problems by training them in a supervised manner with an error back-propagation algorithm. This algorithm is a neural network training algorithm for feeding forward networks where the errors at the output layer are propagated back to the layer before in learning. The error back propagation algorithm is based on the error-correction learning rule and forward and backward passes which are two passes through different layers of the network (Haykin, 1999; Bojadziev & Bojadziev, 1995).

Forward pass

$$V_j(n) = \sum_{i=0} W_{ji}(n)X_i(n) \tag{2}$$

where *n* is the total number of inputs (excluding the bias) applied to neuron *j*, *Wji(n)* is the synaptic weight connecting neuron *i* to neuron *j*, and *Xi(n)* is the input signal of neuron *j*.

Backward pass

$$W_{ji}(n) = \alpha \Delta W_{ji}(n-1) + \eta \delta_j(n)Y_i(n) \tag{3}$$

Where α is momentum constant which controls the feedback loop acting around *ΔWji(n)*, η is a learning rate, *δj(n)* is a local gradient that adjusts the synaptic weights of the network, and *Yi(n)* is the function signal at the output of neuron *j* at iteration n.

6. Solution refining module (SRM)

After the CPDM gives a series of conflicting parameters, both conflicting and correlative parameters will pass to the SRM for tuning. This module carries out decision support in performance optimization to ensure it is acceptable, with the desired measurements. Also, it refines the solution by adjusting some parameters to eliminate the conflicts among local solutions in multi-valued fuzzy logic. A solution-refining engine is embedded in this module, which consists of a fuzzy set, fuzzy rule, fuzzy inference and a knowledge base. 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 remedial action when a performance problem is formed. With the understanding of the rules of customer requirements and by applying them to transform bytes of data into information, an improved quality solution can be attained (Ho et al., 2005). Generally, each rule specifies a relation, recommendation, directive, strategy or heuristics and has the IF (condition) THEN (action) structure. When the condition part of a rule is satisfied, the rule is said to fire and the action part is executed (Negnevitsky, 2005).

Fuzzification is the first step to be carried out in the process of fuzzy inference. After crisp input values are extracted from the suggested performance solution in the PDM, they will be fuzzified over all of the defined membership functions. The rule will be evaluated by taking fuzzified inputs and applying them to the fuzzy rules stored in the knowledge base. The fuzzy rules are stored and defined as conditional statements in IF-THEN form, e.g. **IF** *staging area is medium AND quantity of inbound materials is large,* **THEN** *cross docking time is slightly long.* If a given fuzzy rule has multiple antecedents, the fuzzy operator (AND or OR) 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.

For evaluating the disjunction of the rule antecedents, we use the OR fuzzy operation.

$$\mu_{A \cup B}(x) = \max[\mu_A(x), \mu_B(x)] \tag{4}$$

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

$$\mu_{A \cap B}(x) = \min[\mu_A(x), \mu_B(x)] \tag{5}$$

Aggregation will be performed for unifying the output of all rules. The membership functions of all rules' consequents are previously clipped or scaled, and are combined into a single fuzzy set. As a result, the input of the aggregation process is the list of clipped or scaled consequent membership functions, and the output is one fuzzy set of each output variable (Negnevitsky, 2005).

Defuzzification, which is the last step in fuzzy inference, is a decoding operation that produces a single crisp value as output. There is no unique way to perform the defuzzification. Center of gravity (COG) is the most popular method and is the one adopted in this study. Theoretically, the COG 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:

$$COG = \frac{\sum_{x=a}^{b} \mu_A(x)x}{\sum_{x=a}^{b} \mu_A(x)} \qquad (6)$$

where $\mu_A(x)$ is the membership function values of the fuzzy set A, a and b are the lower and upper boundary values of the aggregated output.

7. Solutions unifying module (SUM)

Figure 4 illustrates an example of the process of SUM which is the module for combining the local solutions which are sent from PQPIM and SRM. In particular, the local solutions from SRM are the refined solutions and the parameters are tuned for preventing conflicting action happening in the logistics operation. These local solutions arrive at a set of unified solutions for solving the original total quality problem and are unified according to the solution unifying rules which are stored in the unifying rule repository. This repository contains the format for unifying the solution in the most appropriate sequence and combination. The sequence affects the type of action to be triggered in a certain time base and some of the actions will be run concurrently in different departments in order to achieve the best performance of the service. The unified solution will then be converted to XML format and sent to the appropriate departments through the web service agent.

8. Case study and findings

The proposed IILS framework has been applied to a third-party logistics company in mainland China that provided outsourced logistics services to other companies for their supply chain management functions. A
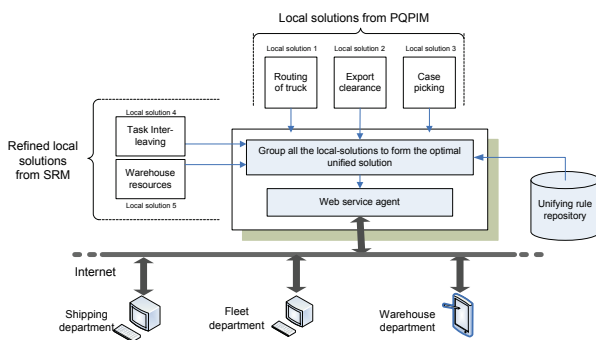

Fig. 4. An operation example in SUM.

prototype software system has been developed based on the proposed framework. It specializes in integrated warehousing and transportation services, and customizes the services to customer's needs based on market conditions, demands, and delivery service requirements for their products and materials. Customers with different requirements are always a concern and challenge in the third-party logistics industry. In order to achieve "the perfect order", the service promise on each occasion needs to be well performed according to the customer's specifications. Also, a proactive quality of service planning should be well-organized to ensure the service outputs from various departments are free of errors. In the proposed approach, the processes of identifying potential problems, finding and studying previous projects, are accomplished by the case base.

There is a case repository in the case-based reasoning sub-system in PQPIM. The library stores a number of cases of previous logistics service plans. Every case has a unique number which is assigned sequentially by the system. The flow of achieving a good quality service plan starts with inputting the information and specifications of the customer's request. The requests will be formulated into a format that the system understands. Then, logistics engineers will input the data of logistics service policy which described individual logistics activities– such as transportation, warehousing, inventory management, production planning /purchasing, and order processing, etc.

The potential quality problems are then given and categorized as product flow, storage management, fleet management and information transfer. For example, a packaging error is classified as an information transfer problem, since the problem is mostly caused by wrong information in packaging instructions. Moreover, picking errors will be regarded as product flow problems, since the failure is due to wrong picking flow and imprecise verification procedures.

For the retrieval of cases in the PQPIM, the information entered such as product type, service type and required specification, are used to filter out irrelevant cases. Similarity analysis is then used to select the cases of close similarity based on the similarity function as discussed in the previous section. Once the most similar case is retrieved, the deduced potential quality problems will be sent, in XML format, to alert the appropriate departments. A snapshot of the scenario of a quality problem division by using IILS is shown in Figure 5.

After DSAM has generated the local solutions, the logistics engineers can make adjustments to the proposed local solutions. Then, the solutions are passed to CPDM for determining the conflict parameters. The conflicting parameters are identified and the solutions will be fine-tuned in SRM. After that, they will be unified to a global
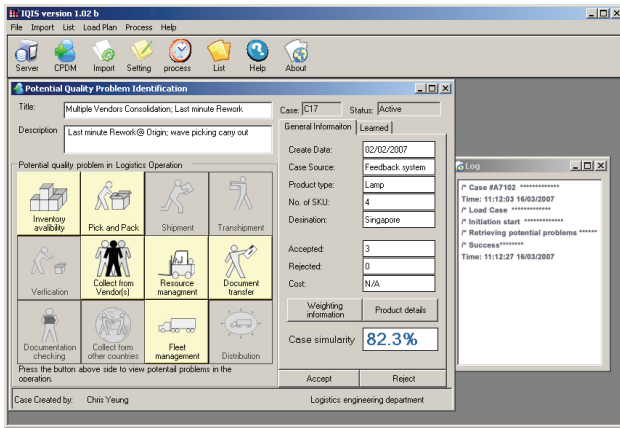
Fig. 5. Screen shot of IILS prototype.

solution in SUM and then passed to various departments through the internet. The final set of solutions will be distributed to authorized decision-makers in various departments. If the decision-makers accept the recommendations, they need to score the related solutions which will be revised for future reuse. Moreover, the clients are invited to give feedback and score the service for further post-purchase evaluation through the logistics feedback system. The level of customer satisfaction will be given by the evaluation of the client's feedback. If the evaluation shows that the performance failure exists in the service, the evaluation data will be transformed as a new case. Then, the case will be stored in the case repository in PQPIM. Figure 6 shows a scenario of solving quality problems by using IILS.

Phase 1.

The first phase involves identifying the specifications of problem characteristics in each department in the enterprise. These specifications can be investigated by examing the elements of pre-transaction, transaction, post-transaction.

i. Pre-transaction elements: Inventory availablity; target delivery date; information capability.
ii. Transaction elements: Convenience of placing orders; order cycle time; order cycle consistency; order fill rate; back-order status; shipment storages; shipment delays; product substuition; routing change; order status; order tracing.
iii. Post-transaction elements: Invoice accuracy; damage; actual delivery dates; returns/adjustments; installation; product replacement.

The development team aims at understanding the critical elements of a process where, if a failure occurs, the quality of the output will be affected. In such a case, understanding these critical potential fail points is very important. Also, the objectives of each department will be identified and the resources will be well prepared. Both of them are needed for building the case repository in PQPIM. After analysis, it is necessary to build the content into a case. In each case of PQPIM, there are a set of
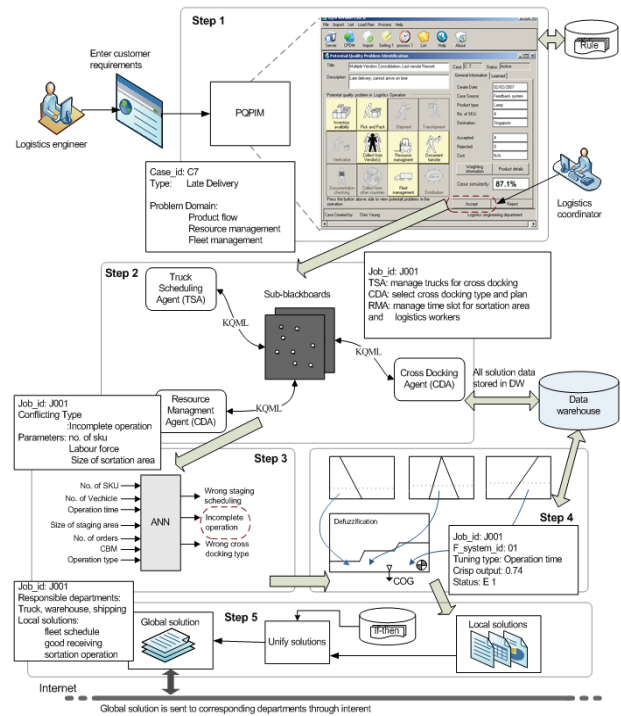

Fig. 6. Scenario of solving quality problems by using IILS.

attributes adequately describing a customer request, nature of the customer, the history of co-operation between a customer and a company, and the previous order information such as the number of stock keeping units (SKU), importing ports, products, and packing instructions. Any individual case has two textual attributes which are: (a) project title, and (b) brief description used for case selection. It also includes classification of quality problems to fulfill the function of identifying all quality problems in the specified products and categorizing them as belonging to the departments responsible for handling them. Moreover, the experts in each department should be interviewed in order to capture their knowledge for defining the fuzzy rule sets in SRM.

Phase 2.

In phase two, a prototype system is developed according to the infrastructure of IILS. The development team devises a prototype package of IILS based on the infrastructural details and the design methodologies mentioned in the phase one. A number of development tools are selected for building up the modules. The main programming tool for system development is Visual Studio.Net. The main components and graphic user interface are developed in C# language. Microsoft SQL Server is the database server used in all repositories. MATLAB Fuzzy Toolbox is used to implement fuzzy inference engine in SRM. Qnet is used for building ANNs of CPDM. A number of DLL programs have been incorporated to enable the "embedding" of both MATLAB and Qnet into the Visual Studio.Net environment. The developed program is then tested to

validate the feasibility of the concept, based on the framework developed.

Phase 3.

Thirdly, the overall evaluation is worked out on the IILS system. It is the test of the integrated IILS for users to determine the possible problems when handling a customer request. Although the main effect of the IILS is the concern about the improvement of logistics operations, there are other possible effects arising from this proposed quality improvement strategy. The main effect is that the implementation of such a system will create a fundamental change of enterprise strategy in organizational operations. As a result of this ever changing market, the enterprise should gain competitive advantages over the rival ones as it is able cope with the customers' changing demands.

Perfect Order achievement is used as a measurement in this case study, which calculates the error-free rate in each stage of a Purchase Order. It captures every step in the life of an order and evaluates the errors per order line. In this paper, a perfect order index is defined as multiplying the percentages of the four elements: (i) warehouse pick accuracy, (ii) on-time delivery, (iii) shipped without damage, and (iv) invoiced correctly. Achieving the perfect order means that each element in the service package satisfies the customer's specifications.
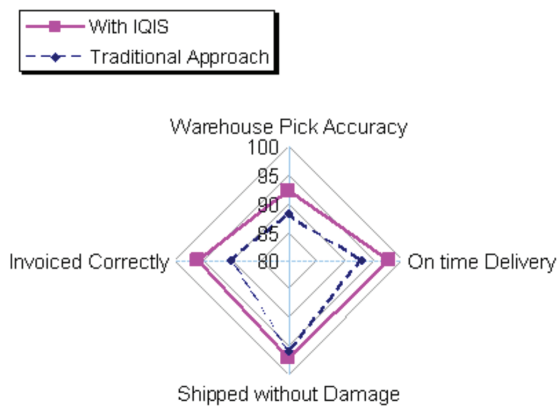

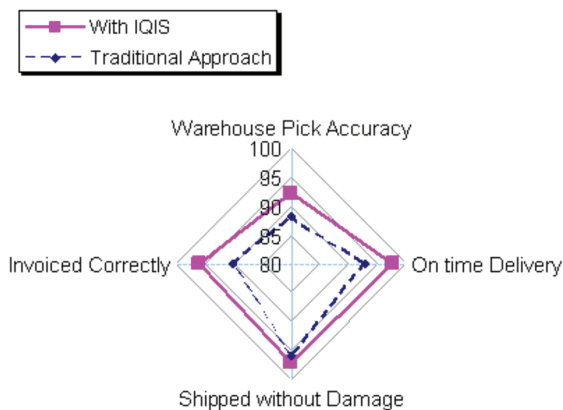Fig. 7. The radar chart of company's pass and current perfect order performance

Fig. 8. The radar chart of the company's past and current performance.

From the figure below, it can be observed that, by using the traditional approach, the resulting perfect order index is 70.6%. In contrast, the index significantly rises up to 83.7% by using the IILS approach. Therefore, our proposed method can enhance the logistics workflow.

In addition, IILS's performance in eliminating quality problems and in preventing quality problems from occurring is evaluated. Thus, those subjective attributes are reserved for the measurable dimensions, which are: (1) Degree of customer satisfaction; (2) Perfect order achievement; (3) Total cost due to quality problems; (4) Time consumed in identifying potential failure points; (5) Response time to customers' orders; and (6) The productivity of the warehouse. Six dimensions in the radar chart are shown in Figure 8.

As can be seen from the radar chart, the overall performance is enhanced. The third-party logistics company finds that the IILS helps identify all of the potential quality problems before providing service to customers in a faster manner compared with the traditional approach.

In addition, the IILS makes use of its problem-solving feature to prevent and eliminate the problems in various activities which cause customer dissatisfaction. Therefore, the total cost due to quality problems is greatly reduced. However, the performance of the IILS in responding to customers' orders is yet to be considered as ideal because the IILS takes time in processing and in sharing data within agents. This cannot provide customers with a fast response. As a result, this is an area which needs to be improved. In summary, a certain amount of improvement can be reflected in a third-party logistics operation and the overall impact due to the deployment of the IILS system can be realized. However, although it may not be justified to have substantial results at the present stage. Further research is needed in the future to verify the proposed approach.

9. Conclusions

In this paper, a new approach, IILS, for logistics industries is proposed for determining potential problems and providing high-quality, reliable, logistics solutions. This infrastructural framework supported with various emerging technologies, also involves developing an agent-based decision support system with special features to cope with problems from various customers' requirements. The major contribution of the proposed system is to enhance customer satisfaction by automating problem-solving procedures in logistics business. Further research on the structural configuration of the system is needed to further enhance its benefits. It is recommended that the researchers utilize innovative information technologies which can help the organization provide complete customer satisfaction. In general, this model

paves the way for a novel approach to deal with logistics problems by using artificial intelligence with the proposed infrastructure. This proposed system can help identify hidden and dynamic problems in the logistics workflow. The logistics workflow and warehouse productivity can also be optimized in this approach. Hence, a higher degree of customer satisfaction can be achieved.

10. References

Ahmed, S. S., Majid, M.S., Novia, H. and Rahman, H. A. (2007). *Fuzzy logic based energy saving technique for a central air conditioning system*, Energy, Volume 32, Issue 7, Pages 1222-1234

Bojadziev, G. and Bojadziev, M. (1995). *Fuzzy sets, fuzzy logic, applications.* World Scientific

Dia, H. (2001). *An object-oriented neural network approach to short-term traffic forecasting.* European Journal of Operational Research 131, 253-261.

Ferber, J. (1999). *Multi-Agent Systems - An Introduction to Distributed Artificial Intelligence.* Addison-Wesley

Gehring, H. and Fischer, T. (2005). *Planning vehicle transhipment in a seaport automobile terminal using a multi-agent system.* European Journal of Operational Research 166, 726–740

Haykin, S. (1999). *Neural Networks: A Comprehensive Foundation*, 2nd ed. Prentice-Hall, Englewood Cliffs, NJ.

Hinckley, C.M. (2001). *Make No Mistake: An Outcome-Based Approach to Mistake Proofing*, Productivity Press, Portland.

Ho, G.T.S., Lau, H.C.W., Lee, C.K.M. and IP, A.W.H. (2005). *An intelligent forward quality enhancement system to achieve product customization.* Industrial Management & Data Systems Vol. 105 No. 3, pp. 384-406

Huin, S.F., Luong, L.H.S., Abhary, K. (2003). *Knowledge-based tool for planning of enterprise resources in ASEAN SMEs*, Robotics and Computer Integrated Manufacturing 19 409-414.

Jiang, Y.C., Yi, P., Zhang, S.Y. and Zhong, Y.P. (2004) .*Constructing agent blackboard communication architecture based on graph theory.* Computer Standards & Interface 27, 285-301.

Karageorgosa, A., Mehandjieva, N., Weichhart, G.. and Alexander, H.A. (2003). *Agent-based optimisation of logistics and production planning.* Engineering Applications of Artificial Intelligence 16, 335–348

Kim, I-S., Son, J-K. and Yarlagadda, P.K.D.V. (2003). *A study on the quality improvement of robotic GMA welding process*. Robotics and Computer Integrated Manufacturing 19, 567–572.

Kwon, O., Im, G.P. and Lee, K.C. (2007). *MACE-SCM: A multi-agent and case-based reasoning collaboration mechanism for supply chain management under supply and demand uncertainties.* Expert Systems with Applications 33, 690–705.

Kolodner, J.L. (1993) *Case-Based Reasoning, Morgan Kaufmann Publishers*, San Francisco, CA.

Lee, V.C.S. and Wong, H.T. (2007). *A multivariate neuro-fuzzy system for forwign currency risk management decision making.* Neurocomputing 70 942-951.

Lim, M.K. and Xhang, D.Z. (2004). *An integrated agent-based approach for responsive control of manufacturing resources.* Computers and Industrial Enginnering 46, 221-232.

Madhusudan, T., Zhao, J. L. and Marshall, B. (2004). *A case-based reasoning framework for workflow model management*, Data & Knowledge Engineering, Volume 50, Issue 1, Pages 87-115.

Negnevitsky, M. (2005). Artificial Intelligence, 2nd ed. Addison-Wesley, Essex, UK.

Nikolopoulos, K. and Assimakopoulos, V. (2003). *The intelligent forecasting information system*, Journal of Industrial Management & Data Systems, Vol. 103 No. 9, pp. 711-26.

Paladini, E.P. (2000). *An expert system approach to quality control*, Expert System With Application, Vol. 18, pp. 133-51.

Oates, T., Prasad, M.V.N. and Lesser, V.R. (1997). *Co-operative information-gathering: a distributed problem-solving approach.* IEE Proceedings Online No. 19971025, (1997).

Olavarrieta, S. and Ellinger, A.E. (1997). *Resource-based theory and strategic logistics research.* International Journal of Physical Distribution and Logistics Management 27 (9/10), 559–587.

Parrott, L., Lacroix, R. and Wade, K.M. (2003). *Design considerations for the implementation of multi-agent systems in the dairy industry.* Computers and Electronics in Agriculture 38, 79/98.

Sonar, R. M. (1999). *Integrating Intelligent Systems using an SQL-database*, Expert Systems with Applications, Volume 17, Issue 1, Pages 45-49.

Samanta, B. and Al-Araimi, S. A. (2001). *An inventory control model using fuzzy logic*, International Journal of Production Economics, Volume 73, Issue 3, Pages 217-226.

Toivonen, J., Vanharanta, A. H., Visa, A. (2006) *Improving logistical decision making – applications for analyzing qualitative and quantitative information*. Journal of Purchasing and Supply Management 12 123-134.

Tsai, C-Y. and Chiu, C-C. (2007). *A case-based reasoning system for PCB principal process parameter identification.* Expert Systems with Applications 32, 1183-1193

Wu, C-H. (2005). *A multi-agent framework for distributed theorem proving.* Expert Systems with Applications 29, 554–565.

Ying, W. and Dayong, S. (2005). *Multi-agent framework for third party logistics in E-commerce.* Expert Systems with Applications 29, 431–436.