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Improving the Knowledge-Based Expert System Lifecycle

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IMPROVING THE KNOWLEDGE-BASED EXPERT SYSTEM LIFECYCLE

by

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ABSTRACT

Knowledge-based expert systems are used to enhance and automate manual processes through the use of a knowledge base and modern computing power. The traditional methodology for creating knowledge-based expert systems has many commonly encountered issues that can prevent successful implementations. Complications during the knowledge acquisition phase can prevent a knowledge-based expert system from functioning properly. Furthermore, the time and resources required to maintain a knowledge-based expert system once implemented can become problematic.

There are several concepts that can be integrated into a proposed methodology to improve the knowledge-based expert system lifecycle to create a more efficient process. These methods are commonly used in other disciplines but have not traditionally been incorporated into the knowledge-based expert system lifecycle. A container-loading knowledge-based expert system was created to test the concepts in the proposed methodology. The results from the container-loading knowledge-based expert system test were compared against the historical records of thirteen container ships loaded between 2008 and 2011.

Chapter 1

INTRODUCTION

Starting in the late 1950's and early 1960's, computer programs were written with the explicit goal of problem solving [Giarratano89]. Knowledge-based expert systems are one manifestation of the applications that trace their roots back to those early programs. Knowledge-based expert systems are computer systems that have expertise in a given domain and are useful when analyzing and processing large amounts of data in a short amount of time [Grosan11] [Dabbaghchi97]. They use knowledge that has been gathered and stored within the knowledge base in order to solve problems in the specific domain for which they were created.

Organizations are always at risk of losing experts in key areas within their business processes due to turnover, illness, or death. Knowledge-based expert systems help alleviate such risks by taking the knowledge obtained by experts, also called problem domain experts, over the course of their careers and storing it within a knowledge base. A knowledge-based expert system can also reduce the amount of time problem domain experts will require to solve problems in the problem domain. A problem domain is a specific area of business process for which a knowledge-based expert system is created to support.

1.1 Knowledge-Based Expert System Components

Knowledge-based expert systems are composed of several independent components. Figure 1, as described by Grosan and Hoplin [Grosan11] [Hoplin90], shows the

independent components and how they work together to solve a problem within the problem domain. The arrows depicted in Figure 1 outline the flow of information throughout the system. The first component is the knowledge base in which heuristic knowledge of the domain experts as well as pertinent facts about the problem are stored [Grosan11] [Hoplin90]. The second component is the inference engine that utilizes strategies from the searching and sorting domains to test the rules contained in the knowledge base on a particular problem. The inference engine accomplishes this by querying information from the knowledge base and applying the returned results. The knowledge acquisition module, the third component, facilitates the transfer of knowledge into the knowledge base for future use [Grosan11] [Hoplin90]. The fourth component is the user interface that allows users to interact with the knowledge-based expert system by presenting the problem to the inference engine and viewing solutions. The fifth component is the working storage which the knowledge-based expert system uses to store information while a specific problem is being solved [Aniba09] and then contains the information pertaining to the solution.

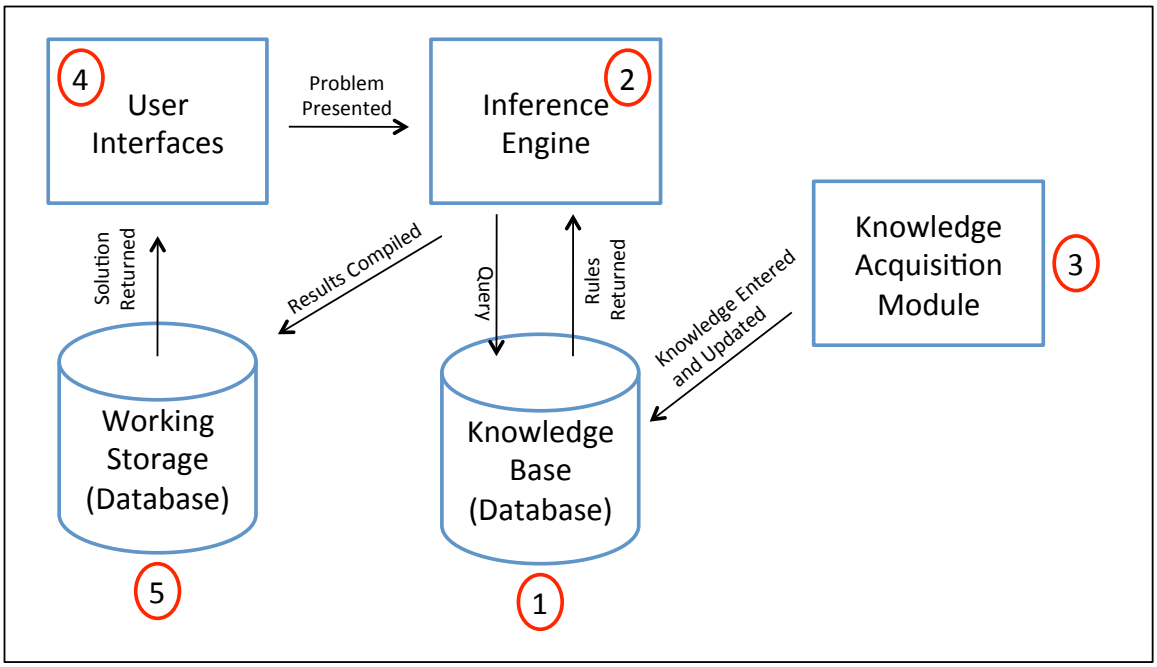


Figure 1: Knowledge-Based Expert System Components

Although there are many advantages to using knowledge-based expert systems, there are some serious disadvantages that can prevent successful development and implementation. Complications during the knowledge acquisition phase could ultimately prevent the system from functioning properly. Furthermore, the time and resources required to maintain the knowledge-based expert system once implemented can detract users from the system and render the system obsolete. Sections 1.2 and 1.3 describe these drawbacks in more detail.

1.2 Barriers to Knowledge Acquisition

One issue pertaining to knowledge-based expert systems is that they are only as accurate as the knowledge contained within the knowledge base. Knowledge acquisition is defined as the process of extracting knowledge from problem domain experts in order to define the required functionality of the knowledge-based expert system. Knowledge

acquisition has been referred to as the “bottleneck in the process of building expert systems” [Golabchi08] [Forsythe89]. The two key groups of stakeholders during knowledge acquisition are the knowledge engineer and the problem domain experts. The knowledge engineer acts as the conduit for extracting domain specific information from the problem domain experts.

The capability of the system is limited by the intelligence and quality of the interviews conducted between the knowledge engineer and the problem domain experts [Mertens04]. Research has been conducted to create standardized frameworks for the knowledge acquisition process. However, the process still relies exclusively on the manual transfer of knowledge from the problem domain experts to the knowledge engineer, thus the success of the process lies entirely on the interviewing capabilities of the knowledge engineer [Wagner86].

Lack of communication is a common problem encountered during the knowledge acquisition phase. There are a multitude of causes starting with issues of missing common terminology and misconceptions made by both the knowledge engineer and the problem domain experts [Hardaway90]. During the interview process the knowledge engineer attaches to a problem domain expert or a group of problem domain experts for a significant amount of time. Personality issues can arise between knowledge engineers and problem domain experts and can create a serious barrier to the knowledge acquisition process [Golabchi08] [Forsyhte89]. Also not all problem domain experts are familiar with information technologies and thus can be reluctant to participate in the development effort. They often do not believe that any automated system can be created to support their complex business processes. Additionally, if the problem domain experts feel that

the knowledge-based expert system can undermine their knowledge and make their jobs seem obsolete, they will be unlikely to assist the knowledge engineer in the development effort.

The knowledge acquisition processes developed were traditionally centered on gathering information directly from the problem domain experts. There were no existing searchable databases containing historical records of problem domain expert's work. Modern experts no longer predominantly use pencil and paper to solve problems. Instead, they use some form of software application created to help them work through the problem and create a solution. The process is still manual because all knowledge still resides with the experts. However, the solutions created using the software based on the manual methods are stored and archived using modern techniques. The modern archival techniques create a searchable historical database or data warehouse of problems and solutions created by experts in the problem domain. The databases can be as simple as spreadsheets stored on a hard drive or can be full-scale database management systems. Traditional knowledge-based expert system implementations do not utilize the information contained in these historical data repositories even though these repositories contain valuable information that could be mined into the knowledge base for future use.

1.3 Issues Associated with Knowledge Base Maintenance

Another issue with knowledge-based expert systems arises in the fact that the domains that these systems are created to function in are dynamic in nature. In order for the system to remain relevant, it must adapt to the changing conditions within the problem domain. Knowledge-based expert systems cannot adapt on their own or create new innovative ways of solving problems [Grosan11] [Hoplin90]. The way that the

knowledge-based expert systems adapt is through maintenance of the knowledge contained within the knowledge base. The difficulty associated with maintaining a knowledge base is dependent on how complex the data structure of the knowledge base is and how well the knowledge acquisition module is constructed. Not all problem domain experts are information technology experts, and therefore knowledge base maintenance can be difficult and time consuming. The knowledge engineer must work with the problem domain experts as soon as a new variable is introduced into the problem domain to ensure the knowledge is updated into the knowledge base properly. This implies that knowledge base maintenance is an ongoing process that can require significant investments of time from both knowledge engineers and problem domain experts after the system has been implemented.

The amount of time necessary to keep up with knowledge base maintenance can present significant problems to an organization. The experts in the problem domain can be extremely busy, can retire, or leave the company for a host of different reasons. Furthermore, information technology personnel are typically stretched thin. They often do not have the necessary resources to train a knowledge engineer to work with the problem domain experts as often as is required to keep up with the maintenance. Thus, problem domain experts are typically left to maintain the knowledge base on their own. This can be frustrating to the problem domain experts and can create a lack of trust in the system as a whole. Problem domain experts would be more apt to revert to the manual method of solving problems as opposed to maintaining the knowledge base.

1.4 Opportunities for Improvement

In order for a knowledge-based expert system to be successfully implemented, the issues discussed above must be mitigated. This thesis will incorporate several tools and techniques not typically associated with knowledge-based expert system development into an improved methodology designed specifically to mitigate the risks described above. The first improvement to the traditional methodology is to enhance the knowledge acquisition phase. Data mining and data warehousing techniques can be utilized to enhance and streamline the knowledge acquisition phase. The second improvement is to change the way knowledge base expert systems are maintained post implementation. By utilizing the power of artificial intelligence to aid problem domain experts, the resources and time required to keep the knowledge base maintained can be drastically reduced.

1.5 Organization

The second chapter of this thesis will provide an overview of the knowledge-based expert system lifecycle. The second chapter will also provide background information on the tools and techniques that will be incorporated into the improved knowledge-based expert system methodology. The third chapter will describe the improved methodology in detail. The fourth chapter will describe an implementation of a knowledge-based expert system using the improved methodology in the container-loading domain. The fifth chapter will present the results from implementing the knowledge-based expert system. The sixth chapter will present the conclusions of this thesis and opportunities for future research.

Chapter 2

OVERVIEW OF KNOWLEDGE-BASED EXPERT SYSTEMS

This chapter provides an overview of the background concepts that support the improved knowledge-based expert system methodology. Section 2.1 describes the traditional knowledge-based expert system lifecycle. Section 2.2 summarizes basic concepts in artificial intelligence and provides specific examples that will be incorporated in the proposed container-loading knowledge-based expert system implementation. Section 2.3 describes the basic concepts associated with data warehousing that will be incorporated in the improved knowledge-based expert system methodology. Section 2.4 outlines extract transformation load (ETL) processes and data mining techniques that can be used to help enhance the knowledge acquisition phase in the improved knowledge-based expert system methodology.

2.1 Knowledge-Based Expert System Lifecycle

The creation of a knowledge-based expert system requires that an appropriate problem statement be constructed. There must be a problem that justifies the amount of effort and cost necessary to implement knowledge-based expert systems for all stakeholders. As with all software implementations, a formal process must be followed to ensure requirements from all levels of an organization are met. Software development methodologies are continually evolving and thus affect how knowledge-based expert systems are developed [Golabchi08]. Modern knowledge-based expert systems are

developed using an iterative development approach, depicted in Figure 2 as described by La Salle [LaSalle90].

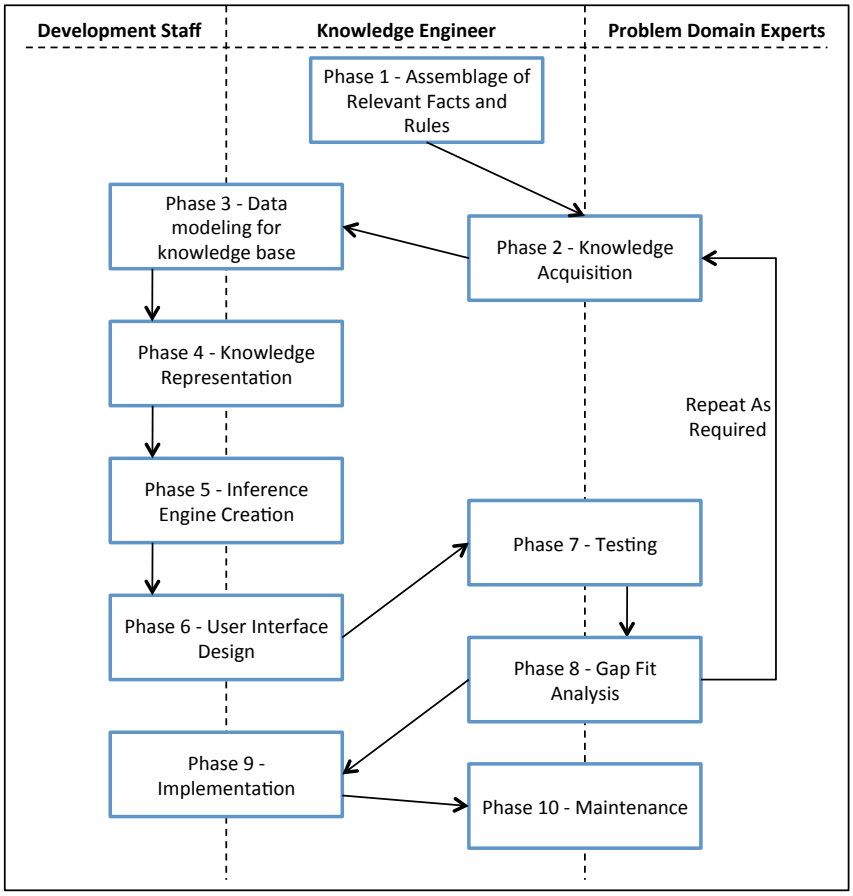


Figure 2: Knowledge-Based Expert System Lifecycle

The key stakeholders during the development and implementation phases of a knowledge-based expert system are the development staff, the knowledge engineer, and the problem domain experts, as depicted at the top of Figure 2. The development staff is a team whose purpose is to construct the components of the expert system as designed by the knowledge engineer. They will have little problem domain expertise and thus must rely on the knowledge engineer to help define the problem domain and associated processes. The knowledge engineer acts as a mediator between the problem domain

experts and the development staff. The knowledge engineer must understand both the technical capabilities of the development staff and also be able to draw out expertise from the problem domain experts. The knowledge engineer must gather system requirements and draw problem domain specific knowledge out of the experts in order for the knowledge base to be filled. In addition to being the end users of the knowledge-based expert system, the problem domain experts understand the requirements and knowledge necessary to construct a knowledge-based expert system.

The first step in the software development lifecycle is for the knowledge engineer to become acclimated with the problem domain, as shown as Phase 1 of Figure 2. The knowledge engineer is then responsible for gathering and interpreting knowledge acquired from problem domain experts into the knowledge base [Grosan11] [Hoplin90]. The knowledge engineer must start gathering information and understanding domain specific terminology prior to conducting any formal meetings or interviews with the problem domain experts. Becoming more acclimated with the domain specific terminology enables the knowledge engineer to communicate with the problem domain experts, and thus aids the knowledge engineer with understanding problem solving in the problem domain.

Knowledge acquisition, Phase 2 of Figure 2, is the process of extracting knowledge from problem domain experts by the knowledge engineer [Grosan11] [Hoplin90]. The goals during the knowledge acquisition phase are to gather system requirements and to document knowledge needed to construct the knowledge base. The knowledge engineer must gather the complete breadth and depth of knowledge from the problem domain experts that will be required to completely solve problems in the problem domain. The

completeness and correctness of the knowledge base is a critical factor to a knowledge-based expert system's success. The knowledge engineer must determine all steps used by problem domain experts in order to solve problems and then turn such steps into detailed requirements for the development staff. Traditionally the knowledge engineer performs a series of interviews with the problem domain experts during the knowledge acquisition phase. The interviews can be conducted using various techniques to facilitate the knowledge transfer from the problem domain experts to the knowledge engineer.

The next phase in development is data modeling for the knowledge base, as shown in Phase 3 of Figure 2. Using the information collected during the knowledge acquisition phase, knowledge engineers use modern data modeling techniques, such as logical and physical modeling, to construct the data structure needed to house the information permanently. As knowledge-based expert systems have evolved, databases have become the standard method of storing and maintaining knowledge in knowledge bases [Grosan11] [Hoplin90].

Once the knowledge acquisition and knowledge base data modeling phases have completed, the knowledge engineer then can begin the knowledge representation phase, as shown in Phase 4 of Figure 2. The knowledge representation phase is defined as the process of translating data into a form useable by a computer system [Hoplin90]. In this phase, the knowledge extracted from the problem domain experts, during the knowledge acquisition phase, is translated into the data structure of the knowledge base. The goal of this phase is to create the data necessary for the initial implementation of the knowledge base.

Knowledge-based expert system methodology is best implemented as an iterative process. Knowledge engineers do not traditionally have experience or training in the processes that make the knowledge acquisition phase successful [La Salle90]. Therefore, the knowledge acquisition, data modeling, and knowledge representation phases can be performed iteratively until the knowledge base represents the complete breadth and depth of knowledge in the problem domain. Iterating through the knowledge acquisition, data modeling, and knowledge representation phases allows for the knowledge engineer to work out the complexities of the problem domain gradually and test the expanding data model [Grosan11] [La Salle90].

The next phase in development is the creation of the inference engine, as depicted in Phase 5 of Figure 2. The main function of the inference engine is to take a problem and search the knowledge base for rules to apply in order to produce a solution. The inference engine should function following the requirements gathered by the knowledge engineer from the problem domain experts. Completeness, correctness, and speed are the three main concepts that must be achieved in an optimal inference engine [Grosan11] [Hanson90]. The inference engine must also be able to traverse all possible combinations of rules in order to design an optimal solution. All solutions created must be correct and reached in a reasonable amount of time. The two types of inference engine implementations are forward chaining and backward chaining [Mattos03]. The problem domain will dictate which implementation the knowledge engineer and development staff select to build for an inference engine.

After the inference engine is created, the next phase of the knowledge-based expert system lifecycle is the creation of the user interfaces, as shown in Phase 6 of Figure 2.

User interfaces allow users to present a problem to the system, view solutions created by the system, and perform maintenance on the knowledge base [La Salle90]. The user interface can be implemented in a variety of ways, including web pages, application forms, or any other modern techniques.

Once the user interfaces are constructed, the system is ready to be tested, as shown in Phase 7 of Figure 2. The most common testing technique is a comparison to a manually solved problem by the problem domain experts. If the solutions vary, the knowledge engineer would have to conduct a gap fit analysis, as shown in Phase 8 of Figure 2. The gap fit analysis would then highlight where the discrepancy originated and the knowledge engineer would either modify the knowledge base or the inference engine algorithms. The testing and gap fit analysis phases are additional iterative processes that allow the knowledge engineer and development staff to gradually evolve towards the final product. Multiple problems spanning the entire problem domain must be analyzed to ensure the knowledge-based expert system's conclusions are compatible with those of the problem domain experts.

Once the knowledge-based expert system can correctly solve problems previously solved by the problem domain experts, the knowledge-based expert system can be used to solve new problems. Initial implementations, Phase 9 of Figure 2, often resemble the testing phase in that the problem domain experts will solve the problem simultaneously to ensure the system is functioning properly. However, after initial implementation success, the knowledge-based expert system is ready to function independently.

After the initial implementation of the knowledge-based expert system, the lifecycle is not complete. Maintenance is required after implementation for knowledge-based expert systems, as shown in Phase 10 of Figure 2. The problem domains for which knowledge-based expert systems are developed are never static. As the problem domains evolv**e,** knowledge-based expert systems must also evolve. The knowledge acquisition module becomes paramount to maintain the system's effectiveness. The problem domain experts must constantly analyze new conditions introduced to the problem domain and adjust the knowledge base accordingly. If the knowledge base is left stagnant and changes to the environment are not incorporated, then the knowledge-based expert system will become outdated, ineffective, and possibly incorrect.

2.2 Artificial Intelligence

The first new concept that will be incorporated into the improved methodology is artificial intelligence. Artificial intelligence is a broad field with the goal of making computers capable of solving problems in a particular domain [Millinton09]. Artificial intelligence theory extends into the realm of human thought and how humans process thoughts to reach conclusions. The term artificial intelligence was coined in 1956 with the earliest work in the field dating back to the end of World War II [Russell03]. The impact of research in artificial intelligence can be seen in everything from Bayesian filters for email, commonly called spam filters, to computer games with realistic algorithms to model game play and everything in between.

One specific area of research is known as the knapsack problem. The classic knapsack or rucksack problem, as shown in Figure 3, is defined as follows: given *n* items, with each

item j having an integer profit p_j and an integer weight w_j, choose a subset of items such that their overall profit is maximized without exceeding a total weight c [Pisinger05].

$$\text{Maximize} \sum_{j=1}^{n} p_j x_j$$

$$\text{Subject to} \sum_{j=1}^{n} w_j x_j \leq C, x_j \in \{0,1\}, j = 1, \dots, n$$

Figure 3: Traditional Knapsack Problem Definition

The traditional knapsack problem and the derived problems based off of the knapsack problem are defined as NP-hard [Khan02] [Russell03]. A problem being designated NP-hard means that an algorithm cannot be created to construct the most optimal solution to the problem in polynomial time. However, researchers have been able to create algorithms that create an approximately optimal solution for NP-hard problems within polynomial time.

The shipping industry has invested heavily in research in solving the knapsack problem [Whelan96]. Algorithms based off the knapsack problem have been developed to support many processes central to the business of shipping. I.D. Wilson's algorithm is one example of how research is being done into the optimization of how containers are stowed aboard a container ship [Wilson99]. Container ships travel in circular routes across the globe with multiple ports of embarkation and debarkation. The goal of Wilson's algorithm is to minimize the number of container lifts needed to unload the containers at each port. Wilson's algorithm takes into account the different types of lifts

that would be required to access each container and identifies which port each container needs to be unloaded. When containers block access to other containers that must be unloaded at a particular port, they have to be lifted and temporarily moved. Each lift costs the shipping company money so reducing the number of lifts at each port is in the best financial interest for shipping companies. Wilson's algorithm can create a load plan that minimizes the cost for a shipping company.

Another area of research related to the knapsack problem in the shipping industry is the automation of the container packing process. Customers order varying numbers of products that must be packed by shipping companies and shipped via standard sized shipping containers. Loading different numbers of products of varying sizes is an area of interest for research in artificial intelligence. Kun He and Wenqi Huang have developed an algorithm to support this process in which a single container with objects of varying sizes is loaded [He10] [Huang07].

He and Huang's algorithm utilizes a caving degree calculation as a metric to determine the best item to load next in the loading process and has shown promising results in reliability and speed. The algorithm, as shown in Figure 4, maintains the available corners within the container in which items may be loaded. Each item that still needs to be loaded is provisionally loaded by the algorithm into each available corner and the caving degree is then calculated. After all items have been provisionally loaded into each corner available, the one that produced the highest caving degree is loaded. The algorithm then updates the list of available corners after loading that particular item. The process then repeats itself until the container is loaded or there are no more items to be loaded.

```
Create list of available items
Create collection of available corners and insert the origin
While there are still available items that can fit in the container {
    For each available corner {
        For each type of available item {
            For each valid item orientation {
                Provisionally pack the item into the corner with the current orientation
                If the item fits in the corner given container size and other objects already
                packed {
                    Compute Caving Degree
                }
            }
        }
        Pack the item with the highest Caving Degree calculation
        Update the list of available corners
        Update the list of available items
    }
}
```

Figure 4: Container-Loading Algorithm

There are three factors taken into account when calculating the caving degree. The first factor is how much surface area of the item being loaded is flat against another surface within the container. The second factor is how far the item is from the other surrounding objects. The final factor is the total volume of the item. He and Huang's algorithm produces an approximation of the best way to load a container, by utilizing the caving degree calculation, without having to test all possible ways of loading a container. This allows the algorithm to function in a reasonable amount of time. He and Huang's algorithm creates an approximate solution to a NP-hard problem with a high degree of reliability.

Each time an item is loaded in He and Huang's algorithm, the collection is updated with new available corners and corners that are now blocked are removed. In order to accomplish the update to the collection of corners, concepts from multivariable calculus

have to be introduced. A corner, according to He and Huang, is defined as an unoccupied point in three-dimensional space where three orthogonal surfaces meet [Huang07] [He10]. Two surfaces, or planes, are called orthogonal if the normal vectors of those surfaces are perpendicular [Stewart05]. Therefore in order for a point, or coordinate, in three-dimensional space to meet the criteria for an available corner according to He and Huang, each surface that contains the coordinate must be evaluated. When an item is loaded, the corner in which the object was loaded into is removed from the collection. The seven other corners of the object being loaded must be evaluated to see if they meet the criteria of an available corner. Furthermore, any existing corners that intersect with the object must be reevaluated to see if they still meet the criteria for an available corner.

The process for evaluating a potential corner, as described in Figure 5, begins by finding all objects that intersect that corner, to include the container walls and floor. Then for each object that intersects the potential corner, the specific plane or planes that intersect the potential corner must be identified. Once each plane is identified, two vectors on each plane must be constructed. By taking the cross product of the two vectors, a normal vector is constructed for each plane. The normal vectors of all the planes that intersect with the potential corner are then tested by calculating the dot product of each combination of normal vectors. If the dot product of the normal vectors of three planes all equal zero simultaneously then the corner meets the criteria identified by He and Huang.

Known Info:

Three points each plane:
$P_0 = (x_0,y_0,z_0)$
$P_1=(x_1,y_1,z_1)$
$P_2=(x_2,y_2,z_2)$

Step 1: Construct 2 Vectors on the Plane for each Plane

$P_0P_1 = (x_1-x_0,y_1-y_0,z_1-z_0) = <a> = (x_a,y_a,z_a)$
$P_0P_2 = (x_2-x_0,y_2-y_0,z_2-z_0) = <b> = (x_b,y_b,z_b)$

Step 2: Construct Cross Product to Create Normal Vector for each Plane

$<a> X <b> = <y_az_b-y_bz_a, z_ay_b-x_az_b, x_ay_b-y_ax_B>$

Step 3: Test Dot product of all three normal Vectors to see if they equal 0

Normal Vector for plane 1 = $<n1> = <n1_x,n1_y,n1_z>$
Normal Vector for plane 2 = $<n2> = <n2_x, n2_y, n2_z>$
Normal Vector for plane 3 = $<n3> = <n3_x, n3_y, n3_z>$

Ensure that:

$<n1> \cdot <n2> = n1_x*n2_x + n1_y*n2_y + n1_z*n2_z = 0$
$<n1> \cdot <n3> = n1_x*n3_x + n1_y*n3_y + n1_z*n3_z = 0$
$<n2> \cdot <n3> = n2_x*n3_x + n2_y*n3_y + n2_z*n3_z = 0$

Figure 5: Orthogonality Test

2.3 Data Warehousing

The second new concept that will be incorporated into the improved methodology is data warehousing. "A data warehouse is a large repository of historical data that can be integrated for decision support" [Teorey11] [Teorey06]. Many organizations today have vast amounts of data yet little information is drawn out of all that data. "Data warehousing is a process, not a product, for assembling and managing data from various sources for the purpose of gaining a single detailed view of part or all of a business" [Gardner98]. Data warehouses leverage the historical data from a company and turn it into useful information to support decision making. The goal of constructing a data

warehouse is to provide fast access to historical data that has been archived in such a manner as to provide useful information for decision making while minimizing the size of transactional databases [Kimball94].

Designing a data warehouse requires a different methodology than is required for traditional transactional databases. Data warehouses are created by using one of two basic structures: the star schema or the snowflake schema. A star schema has one main fact table that is connected to many smaller supporting tables known as dimension tables, as shown in Figure 6 [Teorey06]. Fact tables store the attributes and measures associated with information in the data warehouse. A dimension table stores the additional referential attributes, known as dimensions, for data stored within a fact table [Teorey11] [Teorey06]. Dimension tables are also where hierarchical data is stored that can be used for analysis.

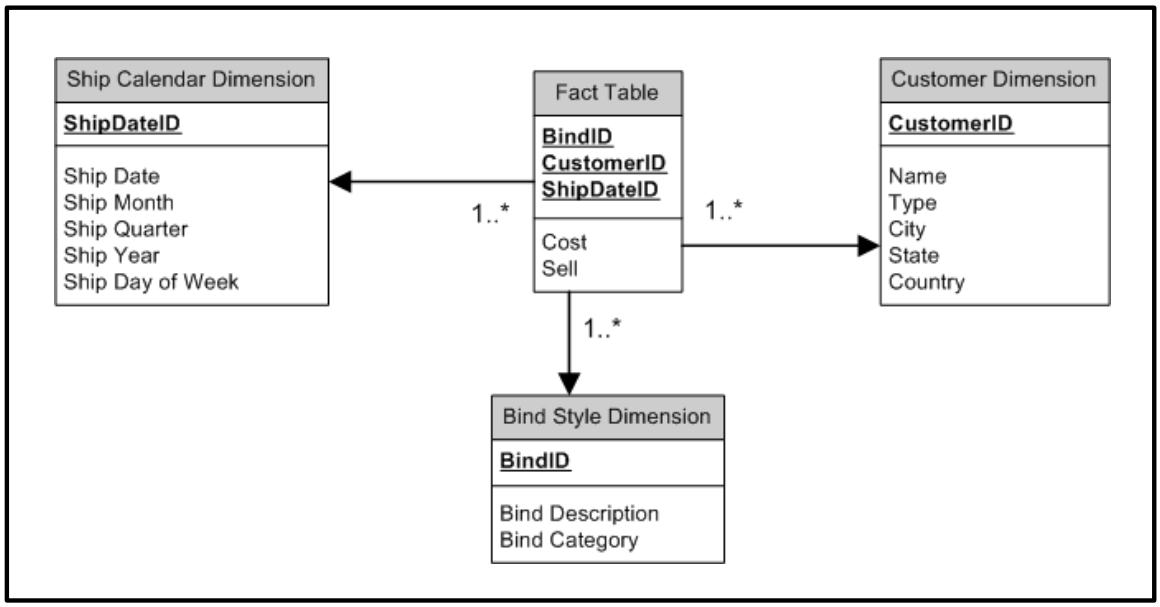


Figure 6: Example of Star Schema

If the supporting dimension tables are normalized to show a hierarchy in the data, as shown in Figure 7, then the schema is known as a snowflake schema. In general, normalizing the dimension tables will slow down processing time, but can be critical in creating a logical separation of data [Levene03]. The goal of data warehousing is to provide historical data for decision support, so the types of data that need to be extracted from the data warehouse will dictate whether a star schema or snowflake schema is used.

Once the schema has been created for the data warehouse, data from one or more operational transactional based databases are processed into a data warehouses in batches at some predefined interval [Levene03]. Data warehouses grow without bounds; this unregulated growth is a deviation from traditional operational databases. Traditional operational databases are kept relatively small with old data being purged periodically. As the data is processed into a data warehouse it is typically translated into an order of larger magnitude, meaning specific details are aggregated in order to support long term trend analysis [Levene03].

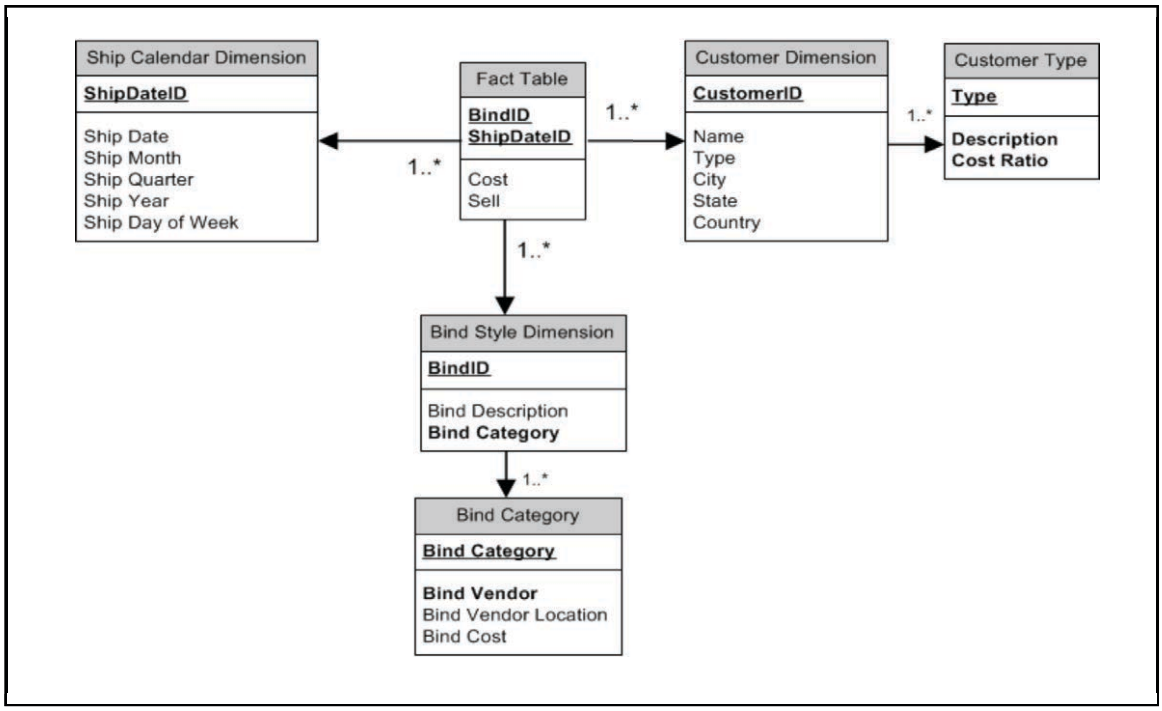


Figure 7: Example of Snowflake Schema

2.4 Extraction Transformation Loading (ETL) Tools and Data Mining

The final concepts that will be incorporated into the improved methodology are extraction transformation loading (ETL) tools and data mining. ETL tools are software components that have the capability to extract data from one or multiple data sources, transform or customize that data, and then insert the transformed data into a data warehouse [Vassiliadis02]. ETL tools are sold commercially or can be created by an organization for their data warehouse.

The extraction phase of the ETL process is where the raw data is pulled out of the various data sources. In order for the extraction process to occur, there must be a temporary storage location with a data model that can support data from the various data sources.

The temporary data storage must be capable of holding data that needs to be transformed into the data model of the data warehouse it is destined for [Skautas11].

The transformation phase of the ETL process begins as the data is extracted out of the temporary storage location and then cleansed and transformed into the data that will be inserted into the data warehouse. The transformation techniques used in this phase are common with data mining. "Data mining is the automatic extraction of implicit and interesting patterns from large data collections" [Romero07]. The process of data mining allows for new patterns to be identified in data. Data mining has been used to discover new patterns and trends in many industries and fields to include medical drug testing, educational trends, and sports analysis. Data mining can be customized as needed to support a variety of data, but there are four basic concepts that are at the center of all data mining applications supporting ETL processes: classification, regression, clustering, and association rule learning.

Classification, also known as supervised learning, is a data mining technique, used during the transformation phase of ETL, in which data is mapped into one of several predefined groups based off of specific criteria [Fayyad96]. The first step in classification is to setup the model for which data will be classified into by defining the different data sets that need to be identified. The second step is to parse the data set and identify which data belongs in which data set [Lutu02]. Classification is used to study financial market trends, credit scoring, geospatial analysis, and many other domains.

Regression is another data mining technique used during the transformation phase that attempts to map relationships between variables [Fayyad96]. Regression techniques are

commonly used in applications when prediction or forecasting is required. The goal of regression is to understand the relationship between a dependent variable and one or more independent variables. Once the nature of the relationship is quantified, it can be used to predict future results based off of environmental changes [Fan06].

A third common technique used during the transformation phase of ETL is clustering. Clustering is defined as a data mining technique that describes a set of data into a finite set of clusters or groups [Fayyad96]. Clustering, also called unsupervised learning, is a technique in which the data has no predefined classifications. Data is placed into meaningful groups based on similarities found during the clustering process [Dalal11]. Clustering has been used in medical research, social networking, and many other domains.

The last common technique used during the transformation phase is association rule learning. Association rule learning is a data mining technique that identifies interesting associations between data attributes [Orriols-Puig08]. The relationships are identified and stored with some measure of interestingness. The interestingness factor is a metric that differentiates how beneficial an association rule is as compared to other association rules. "Association rules are widely used in various areas such as telecommunication networks, market and risk management, and inventory control" [Orriols-Puig08].

Once the data has been transformed, it is ready to be loaded to the data warehouse. The loading process typically takes place when the data warehouse is not in use. After the data is loaded into the data warehouse, it is removed from the temporary storage location. The ETL process as a whole is performed at predefined intervals so the data is loaded in

batches. Research suggests that approximately one third of the effort and budget allocated to an organization's data warehouse is expended on the ETL process [Vassiliadis02].

Chapter 3

METHODOLOGY

There are several concepts that can be integrated into a proposed methodology to improve the knowledge-based expert system lifecycle and components to create a more efficient process. These methods are commonly used in other disciplines but have not traditionally been incorporated into the knowledge-based expert system lifecycle. Figure 8 shows a comparison between a traditional knowledge-based expert system methodology and the proposed knowledge-based expert system methodology described in the following sections.

Traditional Knowledge Based Expert System Methodology	Improved Knowledge Based Expert System Methodology
Phase 1 - Assemblage of relevant facts and rules	Phase 1 - Assemblage of relevant facts and rules
Phase 2 - Knowledge acquisition	Phase 2 – Knowledge Acquisition for the Knowledge Base Data Warehouse
	Phase 2.1 – Data Mining for the Knowledge Base Data Warehouse
Phase 3 – Data modeling for knowledge base	Phase 3 – Data modeling for Knowledge Base Data Warehouse
Phase 4 - Knowledge representation	Phase 4 – Knowledge Representation
	Phase 4.1 – Historical data transformation and insertion into Knowledge Base through scripts or one time use code
Phase 5 - Inference Engine Creation	Phase 5 – Inference Engine Creation
	Phase 5.1 – Create AI algorithm to propose new rules to be added to the knowledge base
Phase 6 - User Interface Design	Phase 6 – User Interface Design
Phase 7 – Testing	Phase 7 – Testing
Phase 8 - Gap fit analysis	Phase 8 – Gap Fit Analysis
Phase 9 – Implementation	Phase 9 – Implementation
Phase 10 – Maintenance	Phase 10 – Maintenance
	Phase 10.1 – Artificial Intelligence maintenance through trend analysis of rules being rejected

Figure 8: Methodology Comparison

Section 3.1 describes how modern data modeling, ETL processes, and data mining techniques for the knowledge base data warehouse can be used to enhance the knowledge acquisition process. Section 3.2 describes how artificial intelligence can be used to reduce the effort required to maintain the knowledge base of an expert system. Integrating these concepts with the traditional knowledge-based expert system lifecycle will result in the proposed knowledge-based expert system lifecycle, as depicted in Figure 9.

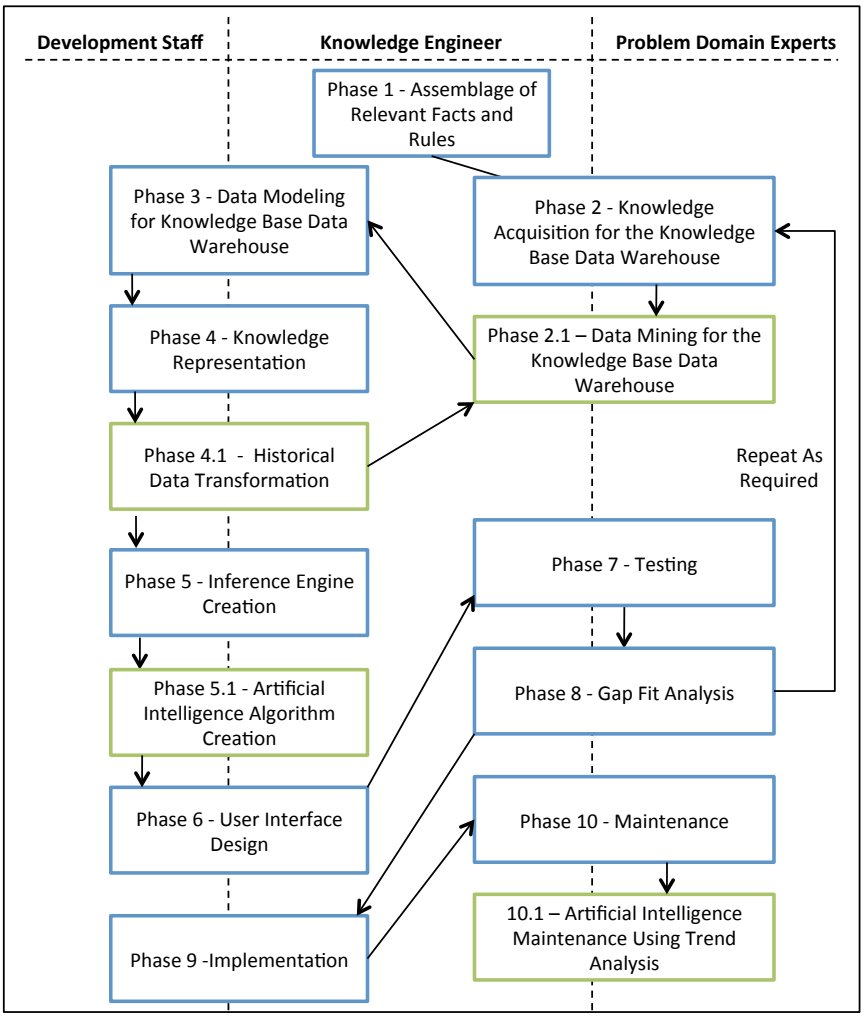


Figure 9: Proposed Knowledge-Based Expert System Lifecycle

3.1 Enhanced Knowledge Acquisition

Once the logical and physical modeling phases of knowledge-based expert system construction have been completed, the knowledge engineer must start to extract knowledge from the problem domain experts in order to fill the knowledge base. In addition to the traditional interview techniques, ETL techniques can be used to extract knowledge from the data contained in historical databases or data warehouses, shown as Phase 2.1 in Figure 9. This ETL process can be used to augment the knowledge acquisition process from the problem domain experts. Depending on the knowledge base construction and the structure of the historical database or warehouse, one or more data mining techniques could be utilized during the transformation phase of ETL: clustering, classification, regression, summarization, or association rule learning [Han12]. Knowledge-based expert systems utilize rules contained within the knowledge base to solve problems. Therefore, association rule learning typically will be used during the knowledge acquisition phase. However, the other data mining techniques can be used to determine which rules are worth keeping and which rules should be discarded. By analyzing the problems and solutions contained within the historical database or data warehouse, the knowledge engineer can extract vast amounts of knowledge used by the experts in the past.

Once the data have been extracted, it must be transformed into a new structure so that it can be inserted into the knowledge base, shown as Phase 4.1 in Figure 9. Database scripts or one time use code can be created to complete the transformation and loading processes. The knowledge representation process can now transfer large amounts of historical data into the knowledge base data warehouse. Historical data is processed into

the knowledge base, which will now be implemented as a data warehouse, for storing facts gathered from the historical data of a transactional database. Data warehousing techniques can be employed in this phase to produce a rich data warehouse that will provide fast access to historical data for the inference engine.

Through ETL techniques and by utilizing the historical data sources containing problems and solutions in the problem domain, the knowledge acquisition process can be enhanced and streamlined. Data models can be verified for accuracy using historical data, meaning the construct of the new data model can be verified by extracting historical data into the new data model. If the data cannot be extracted or information is lost during the extraction, then the data model needs to be modified. Furthermore, gathering the information for the initial starting point for the knowledge base can be simplified and would require less time from the problem domain experts. This will reduce the number of interviews required by the knowledge engineer with the problem domain experts and increase the reliability of the knowledge gathered. This process will help to reduce the bottleneck that is traditionally encountered during the knowledge acquisition phase of knowledge-based expert system development.

3.2 Integration of Artificial Intelligence for Knowledge Base Maintenance

Using the specific requirements of a problem domain, a rule-generating algorithm based on artificial intelligence techniques will create new rules to be added to a knowledge base, as shown in Phase 5.1 of Figure 9. The goal of this rule-generating algorithm is to take a partially completed solution where no existing rules can be used to complete the solution, and then construct potential rules that can be added to the knowledge base to

complete the solution. This implies that the manual process of updating the knowledge base is now an automated process.

The algorithm would combine techniques from the specific problem domain and the artificial intelligence domain, thereby allowing the algorithm to construct new potential rules. The new rules could then be ordered from the most optimal solutions down to the least optimal solutions. The problem domain experts would then be able to review each of the potential additions to ensure their validity. Once the problem domain experts approve a set of rules that will allow the knowledge-based expert systems to completely solve the problem, it will be presented to the user as a complete solution.

Once the knowledge-based expert system has been created, all the rejected rules will be stored in the data warehouse for use in future analysis. As part of the maintenance phase, rejected rules can be analyzed by the knowledge engineer and development staff to see if there are any significant trends in the data, signified in Phase 10.1 of Figure 9. If trends are discovered then the algorithm will be modified so that these types of rules are not presented to the users again. This process will provide the empirical data that will allow for the algorithm to be updated as the system and the problem domain evolve.

As artificial intelligence is incorporated into the knowledge-based expert system, the problem domain expert's responsibility becomes only to approve modifications to the knowledge base that have been created by the rule-generating algorithm. The algorithm will reduce the amount of effort necessary to keep the knowledge base maintained, and will also eliminate the need for a manual knowledge acquisition module. Another inherent benefit lies in the fact that in order for the algorithm to prioritize the potential

solutions, a metric must be established. The rule metric will determine a ranking method for the rules contained within the knowledge base. Ranking rules will allow the inference engine to select the highest ranking rules first and allows the knowledge engineer to establish minimum rankings for rules within the knowledge base. The proposed algorithm could be used on the existing rules in the knowledge base. Statistical analysis could then be performed on the quality of the knowledge in the knowledge base. Knowledge deemed statistically poor could then be removed from the knowledge base by the system.

The most logical place to incorporate the statistical measure of historical data is in the inference engine. The inference engine should be setup to allow for a configurable minimum value based off the rule metric for rules to be used when solving problems. During the testing and gap fit analysis phases, the same problems can be solved using different minimum values. The results can be recorded and analyzed to determine what the long-term minimum value should be for the inference engine. Since the knowledge base is now created as a data warehouse, it will be able to accommodate all the historical data and still be able to function within a reasonable amount of time.

3.3 Advantages of the Improved Methodology

The proposed knowledge-based expert system lifecycle, as shown in Figure 9, utilizes the benefits of a variety of disciplines that are not traditionally associated with knowledge-based expert systems. By combining ETL processes, data mining, and data warehousing, the knowledge acquisition process is streamlined. It reduces the potential for human error between the knowledge engineer and the problem domain experts. The vast amounts of historical data for an organization can be turned into information that the

knowledge-based expert system can draw upon to solve problems. Integration of artificial intelligence reduces the maintenance required for the knowledge base. The rule metric determined when creating the rule-generating artificial intelligence algorithm is incorporated into the inference engine to allow for a true statistical analysis on the historical data to determine which rules should be used in the future. All these changes coupled together will result in a faster and more effective design and implementation process for knowledge-based expert systems and a much less complicated maintenance process post implementation. Figure 10 depicts the components of the proposed expert system. The knowledge base is constructed as a data warehouse providing fast access to historical data for the knowledge-based expert system. The artificial intelligence module is now acting as the automated means to keep the knowledge base current post implementation, as opposed to the traditional manual methods.

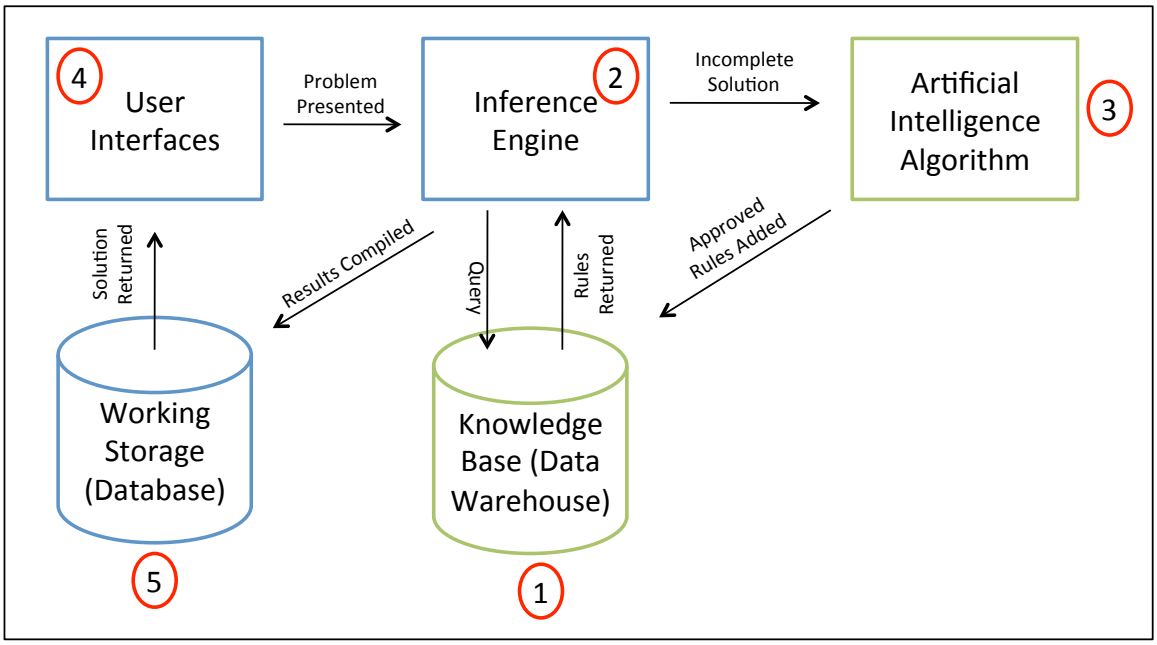


Figure 10: Proposed Knowledge-Based Expert System Components

Chapter 4

IMPLEMENTATION

Both civilian and military organizations transport materials across the globe using standard shipping containers. The process of loading containers with the materials needing to be shipped is currently a manual process that could be enhanced with the implementation of a knowledge-based expert system. This chapter will describe the process of creating an improved knowledge-based expert system for the container-loading domain.

4.1 Phase 1 – Assemblage of Relevant Facts and Rules

Civilian and military transportation organizations ship equipment and supplies across the globe using standard sized shipping containers. In some cases, the military leaves equipment afloat as a strategic asset to enable streamlined emergency responses. Due to shelf life limitations, calibration requirements, and maintenance requirements of the equipment and supplies, the equipment must be periodically unloaded and maintained.

As ships come into port for their regularly scheduled maintenance, they must be completely unloaded. All containers, once unloaded, are emptied and their contents are sent to designated areas for maintenance. Once the maintenance is complete, all equipment and supplies are sent back to a central warehouse where they will be reloaded into standard shipping containers. The total number of containers that will fit aboard a ship is a predetermined quantity. The equipment and supplies required to support the military's capability exceeds the available space aboard each ship. Only equipment and

supplies with a high priority are loaded onto the ship whereas those with a lower priority are left behind. The optimization of space inside each container is important because the more compactly a container is loaded, the more equipment and supplies can be loaded on each ship.

The process of reloading the standard shipping containers is a manual process. Container-loading experts place equipment and supplies on the warehouse floor in piles. Once the container-loading experts feel that the pile represents a fully loaded container, a new pile is started for the next container. The piles are then loaded by a forklift into each container one by one and sealed. Information regarding the equipment and supplies in each container loaded is manually collected and entered into a transportation system. The containers are then staged until the ship is ready to be loaded.

The container-loading experts understand how to correctly load equipment and supplies into a container and all the potential issues in loading a container as well. The loading of each container is treated as an independent process. All the knowledge required to create a container load resides with the container-loading experts. There is no database or data repository that contains the specific information about how to load a container. Therefore the quality and compactness of the container loads resides strictly on the knowledge of the container-loading experts. These military processes are paralleled in the civilian sector as well. Many transportation companies must prioritize and load cargo into containers to be shipped. Thus, creating a container-loading knowledge-based expert system will be beneficial to both the civilian and military transportation organizations.

4.2 Phase 2 – Knowledge Acquisition for the Knowledge Base Data Warehouse

The goal of the knowledge acquisition phase was to learn all the different types of rules that the container-loading experts use while loading containers. Each individual combination of equipment and supplies, meaning each potential rule in the problem domain, did not have to be identified. Traditionally every possibility of how a container could be loaded would have to be identified in this phase. However, because the improved methodology incorporates data mining historical data for the inference engine coupled with the artificial intelligence, this was not necessary.

After meeting with the container-loading experts, two basic principles were identified as the main limiting factors when loading a container. The first principle states that not all equipment and supplies can be stacked inside a container. Due to the weight, sensitivity, and several other factors, certain items cannot be placed on top of any other items. However, some items can be loaded anywhere in a container, including being on top of other items. This principle implies that the overall compactness of loading a container will reside in properly integrating items that can be stacked with items that cannot be stacked. Furthermore, once all the items that can be stacked have been loaded, the overall compactness of the containers being loaded is reduced because the remaining items cannot be loaded on top of each other. The second principle states that some items can be stored in a rotated configuration. This concept is important because an item could be rotated to potentially fit into a space it would not fit into in its original orientation, and can increase the overall compactness of a container. Container-loading experts were able to create lists of both the items that can be stacked and the items that can be rotated.

4.3 Phase 2.1 – Data Mining for the Knowledge Base Data Warehouse

As described above, the content level detail for each container loaded is entered into a transportation system. This implies that there is a historical record of each container that has been loaded. Each record in the transportation system, as shown in Figure 11, has a plan identifier, serial number and a national stock number (NSN). The plan identifier designates which ship the container was loaded onto, and the NSN, a unique thirteen-character code, identifies every different item in the military's inventory. Each record also has a field for the parent serial number and the parent NSN. When an item is loaded into a container, the serial number and NSN of the container are put into these fields. The records for the containers have the same information in the serial number and NSN fields as the parent serial number and parent NSN fields.

Ship Identifier	Serial Number	NSN	Parent Serial Number	Parent NSN
Ship 1	1	1111111111111	1	1111111111111
Ship 1	2	2222222222222	1	1111111111111
Ship 1	3	2222222222222	1	1111111111111
Ship 2	4	1111111111111	4	1111111111111
Ship 2	5	2222222222222	4	1111111111111
Ship 2	6	3333333333333	4	1111111111111

Figure 11: Example of Transportation System Data Set

The data from the transportation system was extracted and stored in its raw form. The transportation system also contains a technical data table, with the length, width, height, weight, and description of each NSN. The data from the technical data table was also extracted from the transportation system in its raw form.

4.4 Phase 3 – Data Modeling for the Knowledge Base Data Warehouse

Once all the historical data was extracted from the transportation system, a data model was constructed to store the data. The data model for the data warehouse, as shown in Figure12, had to be setup in order to enable the inference engine to access the data. The data warehouse was created by utilizing SQL commands on a Microsoft SQL Server 2008 implementation. First, as shown in Figure 12, a fact table was constructed to hold the unique rule identifier, the unique item identifier, the time when the rule was entered, the person who entered the rule, and the quantity of the item. An item dimension table was then constructed to hold the description of the item, the dimensional data of the item, whether the item could be loaded in a rotated configuration, and whether the item could be stacked. The rule dimension table was created to hold a description about the rule and the total volume of all the items that make up the rule. The time dimension table holds the specifics regarding the date and time which is used for creation of a rule. Finally, the person dimension table was constructed to hold the information about the users of the system.

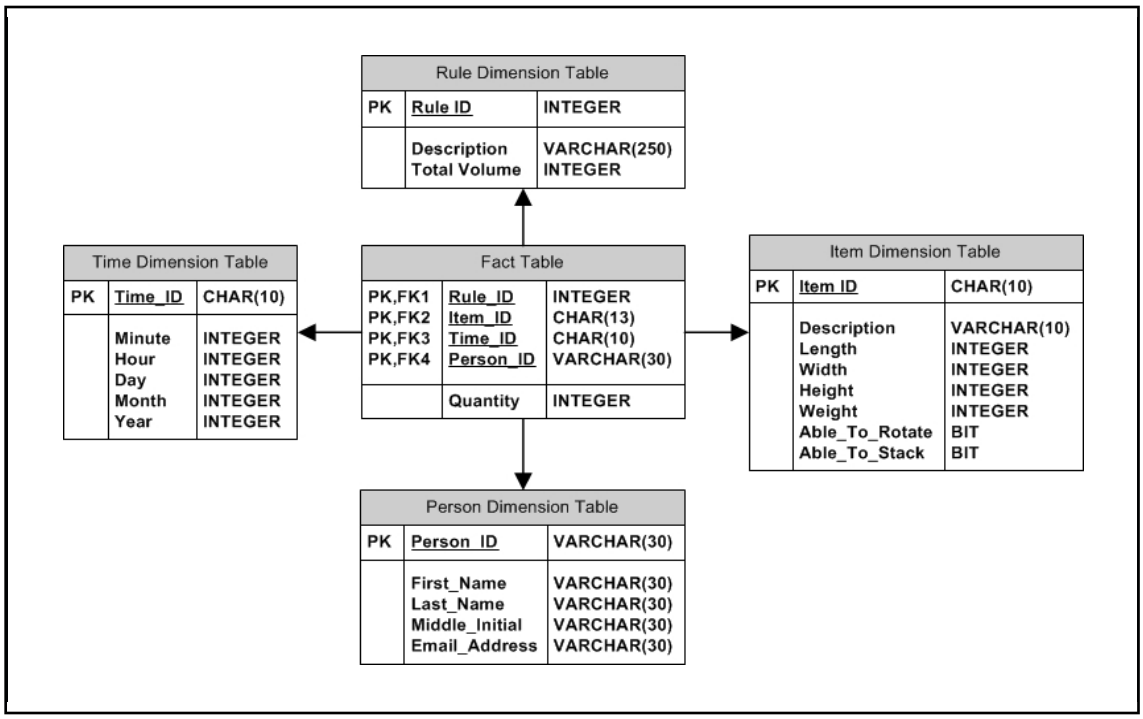


Figure 12: Data Warehouse Schema

4.5 Phases 4 and 4.1 – Knowledge Representation and Historical Data Transformation

The proposed methodology strengthens the traditional knowledge representation phase. The process for executing this phase was a multistep. The first step of the knowledge representation phase was to transform and load the historical data that was extracted from the transportation system into the newly constructed data warehouse. In order to accomplish the transformation and loading, one time use code was created. The code was written in Visual Basic and had two main processes: to load the unique item information into the item dimension table and to populate the rule dimension and fact tables with the historical data once transformed. Since the transportation system does not maintain a user account associated with the data, a user was entered into the person dimension as "Historical Data" in order to support the data loading.

The first step in the knowledge representation phase was to load the information from the transportation system's technical data table into the item dimension table. No transformation was required of this data except that all items were temporarily loaded with the rotate and stack fields set to false. The information for those fields did not reside in the transportation system; the container-loading experts provided the information during the knowledge acquisition phase. Once the item dimension table was populated, manual SQL scripts were created to update the rotate and stack fields on appropriate records using the information provided by the container-loading experts.

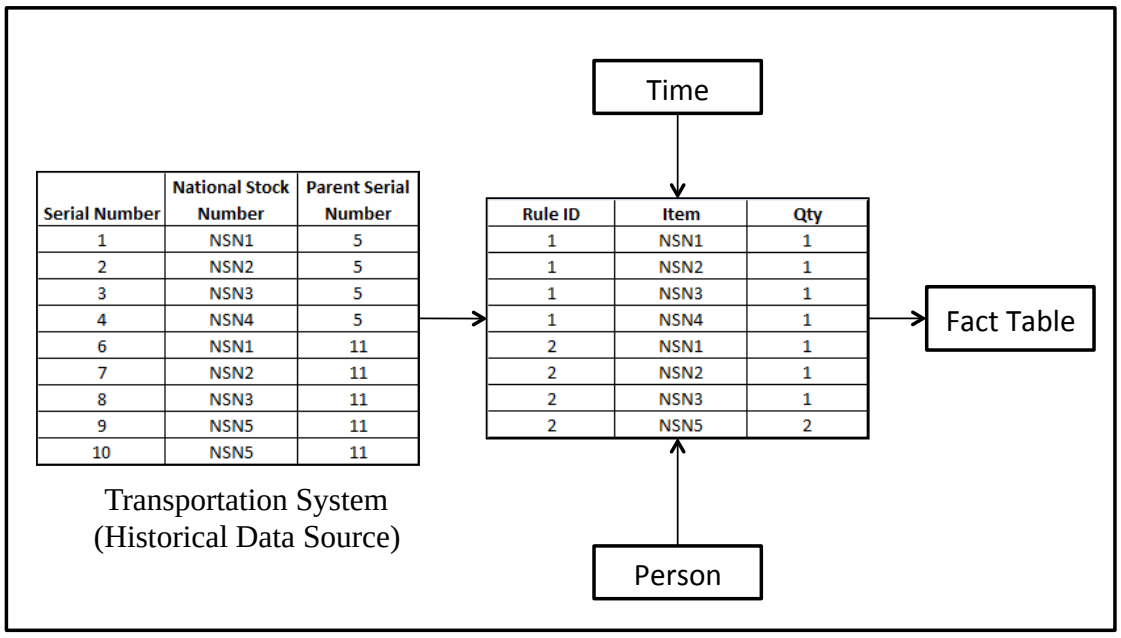


Figure 13: Associate Rule Learning Process

The second step in the knowledge representation phase was to load the information for the rule dimension and fact tables. The data mining technique used to transform the data was association rule learning. As shown in Figure 13, each container from the extracted data was turned into a unique rule with the quantities summed by each distinct NSN. The

time dimensional data and person dimensional data were then added to the transformed data. The data was then in a compatible format with the fact table in the data warehouse and was loaded. The final step was to create an entry in the rule dimension table for each distinct rule in which the total volume of all items pertaining to each rule was summed and added.

4.6 Phase 5 – Inference Engine Creation

The inference engine for the container-loading knowledge-based expert system was implemented as a forward chaining inference engine. Forward chaining inference engines start with the problem and select rules from the knowledge base in order to work forward to a solution. The inference engine was created as its own class using Visual Basic in order to isolate and encapsulate the functionality. A supporting class was created to hold information pertaining to the actual containers being loaded using the rules from the knowledge base by the inference engine. Another supporting class was created to store the information for an object that was being loaded into a container.

As shown in Figure 14, the inference engine starts by selecting all the equipment and supplies from the problem presented into a collection ordered from the equipment or supplies with the largest volume to ones with the smallest volume. Then for the equipment or supply with the largest volume, all rules that contain that item are pulled out of the knowledge base. Only the rules that represent a container that will be filled above the minimum percentage set for the problem will be used. The inference engine was created so that problems can be solved with different minimum values for historical data that will be used. Therefore the same set of data, representing a problem, could be

solved with different minimum values which enabled the long-term minimum threshold to be identified using empirical data during the testing and gap fit analysis phases.

```
Load all items from the problem into the Items Collection from largest to smallest
For each item in the Items Collection {
    Select all rules from the Knowledge Base that contain the item into the Rules Collection
    Remove rules that are below the minimum value set for the problem
    Order the rules in the Rules Collection from the most optimal to least optimal
    For each rule in the Rules Collection {
        If there are no more items to spread {
            Inference Engine Completely Solved the Problem
        }
        If all the other items in the rule are in the Items Collection {
            Remove the items from the Items Collection
            Add the items to the solution as a loaded container along with the Rule Identifier
            Try the rule again until it cannot be used any more
        }
    }
}

If items remain in the Items Collection {
    Inference Engine Could Not Completely Solve the Problem
} Else {
    Inference Engine Completely Solved the Problem
}
```

Figure 14: Inference Engine Process

The rules are ordered by the percentage of a fully loaded container that each rule represents from largest to smallest. Starting with the first rule, the inference engine will check to see if the other items in the rule exist in the items collection. If the other items exist, those items are moved from the items collection to the solution along with the rule identifier as a loaded container. The rule is then tested to see if it can be used again. If the rule cannot be used because the other items are not in the items collection, the next rule is tried and the process repeats until there are no items left in the items collection or

there are no more rules for that item. Once all the possible rules for that item are tested, the process repeats itself on the next largest item in the items collection. The inference engine forward chaining process will stop once all the items are removed from the items collection. If all the items cannot be removed from the items collection then the inference engine cannot completely solve the problem with the knowledge contained within the knowledge base. The items that remain in the items collection are passed into the artificial intelligence algorithm in order to create new rules to complete the solution.

4.7 Phase 5.1 – Artificial Intelligence Implementation

The next phase in the development of the container-loading knowledge-based expert system is the creation of the artificial intelligence algorithm that will be used in conjunction with the inference engine. Similar to the inference engine, the artificial intelligence algorithms were created as their own class using Visual Basic. The artificial intelligence algorithm will accept a list of items from the inference engine that could not be loaded into a container using the rules in the knowledge base. The artificial intelligence algorithms were created with the capability to analyze the list of items presented to it and construct a list of potential rules that can be added to the knowledge base in order to complete the solution.

He and Huang developed a three-dimensional single container packing optimization algorithm [Huang07] [He10], as described in Chapter 2, which was implemented to support the knowledge base maintenance. He and Huang's algorithm was developed independently from any system and is designed to load items sequentially by provisionally loading each remaining item and testing to see which one is the best fit. The original algorithm was slightly modified, shown in red in Figure 15, in order to

function properly with the inference engine. The first modification allowed the algorithm to rotate items into different configurations. Rules contained within the knowledge base tied to each item will dictate whether an item can be rotated or not. The second modification will allow the algorithm to load multiple containers instead of just one. The modifications to He and Huang's algorithm provide the ability to construct all necessary potential rules to be added to the knowledge base that will allow the knowledge-based expert system to complete the entire solution automatically without user input.

He and Huang's algorithm was simple to implement and the changes to the algorithm were easily incorporated. The Caving Degree Calculation was a straightforward calculation and thus easy to implement as its own class as well. However, there was one part of the algorithm that was difficult to implement. As described in Chapter 2, the algorithm maintains a collection of corners that items can be loaded into. In order to support all the calculations necessary to accomplish the orthogonality test, as shown in Figure 5, supporting classes had to be created. A coordinate class was created to store information about the X, Y, and Z information required to define a three-dimensional coordinate. A class was also created to store information about a plane in three-dimensional space, and to create the vectors and normal vectors for each plane. Also a three-dimensional object class was created to store the information about the three-dimensional objects being loaded by the artificial intelligence algorithm.

```
Create list of available items
For current container {
    Create collection of available corners and insert the origin
    While there are still available items that can fit in the container {
        For each available corner {
            For each type of available item {
                If the corner is on the ground or the item can be stacked {
                    Provisionally pack the item into the corner with the original orientation
                    If the item fits in the corner given container size and other objects already packed {
                        Compute Caving Degree
                    }
                    If item can be rotated {
                        For all other orientations {
                            Provisionally pack the item into the corner with the current orientation
                            If the item fits in the corner given container size and other objects already packed {
                                Compute Caving Degree
                            }
                        }
                    }
                }
            }
        }
        Pack the item with the highest Caving Degree calculation
        Update the list of available corners
        Update the list of available items
    }
    Create new potential rule to be added to the data warehouse based on current results
    Create new container
}
```

Figure 15: Artificial Intelligence Algorithm

4.8 Phase 6 – User Interface Design

The user interfaces for the container-loading knowledge-based expert system were constructed as web forms in Visual Basic. The web forms had access to all the classes corresponding to the inference engine, the artificial intelligence algorithms, and all supporting classes. The logic created on the user interfaces included the ability to create a problem, the ability for the system to create a solution for a particular problem, and the

ability to view the solution. All the logic for solving problems was encapsulated into the inference engine and artificial intelligence classes.

Several web forms were also created in order to generate statistical comparisons. The first form compares problems solved by human experts to the same problems solved by using artificial intelligence. The comparison was designed as a control to see how well the artificial intelligence algorithm operates. The second form compares the solutions of the same problem with different minimum values for the inference engine, which allows for statistical analysis to be performed identifying what the long-term minimum value should be.

4.9 Phase 7 – Testing

The first step in the testing phase was to evaluate how the artificial intelligence algorithms functioned independently. Problems that had been previously solved by container-loading experts were recreated in the container-loading knowledge-based expert system. Those problems were then solved using only the artificial intelligence algorithms. No rules from historical data were used. This allowed for a controlled comparison between the capabilities of the container-loading experts and the artificial intelligence. In order to quantify the value of adding historical data, the capability of the artificial intelligence algorithms had to be verified. The results of this comparison are discussed in detail in Chapter 5.

The second step in the testing phase was to determine the minimum value for the inference engine to use when using historical data in problem solving. Since shipping containers are a standard size, the volume of the contents of historical loads can be

summed up and divided by the volume of the container to determine the percentage of the container that is full. The testing process was setup to solve the same problems that had previously been solved by the artificial intelligence alone with using both historical data and the artificial intelligence together. Each problem was solved ten different times using different minimum percentages for historical data. Solving the same problem with different minimum percentages allowed for statistical analysis to be done on what the best long-term minimum percentage should be for the system. The goal in setting the minimum percentage is to best use the combination of historical data and artificial intelligence to create an optimal solution. The results of this comparison are discussed in detail in Chapter 5.

4.10 Knowledge-Based Expert System Software

The testing phase was accomplished by using the software as described throughout in Chapter 4. This section will show examples of the software and how the results discussed in Chapter 5 were created. The software was setup to allow multiple users access to the system. Figure 16 shows a screen shot of the login screen.

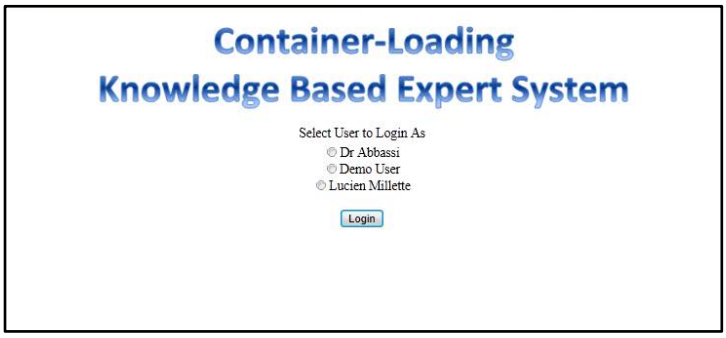


Figure 16: Login Screen

Once a user has been authenticated to the system, the main screen will load. The main screen shows all the current problems that have been created in the system, as shown in Figure 17. All the details about each particular problem are shown after the name of the problem, to include whether to use historical data in solving the problem and what the minimum percentage should be for the inference engine if historical data is used. Solutions to problems that have already been solved can be viewed by selecting the last column. If the problem has not been solved then the last column is where users select to have the system create the solution for that problem. New problems can also be created by utilizing the form at the bottom of the screen.

Figure 17: Main Screen

If a problem has not been solved, the name of the problem is displayed as a hyperlink. By selecting the hyperlink a page will load where problem details can be modified, as shown in Figure 18. The problem details page allows equipment and supplies to be

added or removed from a problem. By utilizing this interface, each problem corresponding to a ship loaded by the container-loading experts was created.

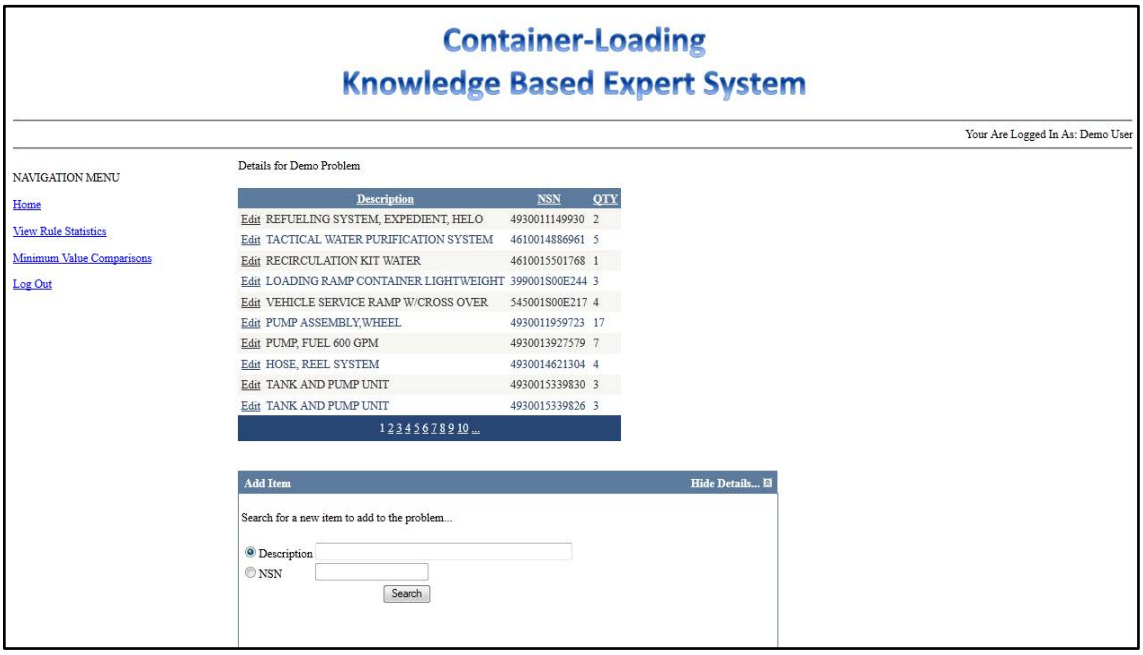


Figure 18: Problem Details Page

First, a problem was created that corresponded to a ship that was loaded by the container-loading experts. It was then copied ten times using the copy button, as shown in Figure 17. Each copy was setup with a different minimum value for the inference engine to use for historical data, thus allowing for the same problem to be solved with different minimum values.

When all the problems were created and configured properly, they were then solved. If the problem was setup to use historical data, the inference engine would use as many rules as possible from the knowledge base data warehouse that were above the minimum value. If the problem could not be completely solved using those rules, the user would be prompted to use the artificial intelligence to complete the solution, as shown in Figure 19.

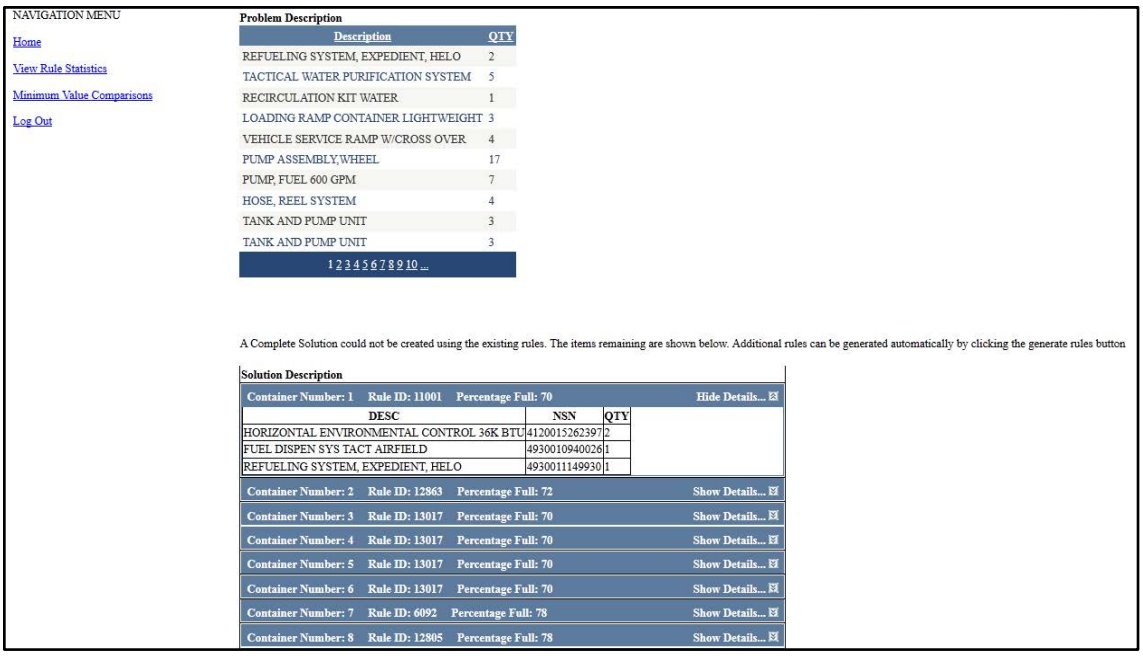


Figure 19: View Solution Page

The artificial intelligence would then construct the rules needed to be added to the knowledge base in order to complete the solution. If the problem was not setup to use historical data, then the artificial intelligence would create the rules necessary to solve the entire problem. Users could review each new potential rule independently in order to approve or reject them, as shown in Figure 20. Users could also select a button to add all the potential rules to the knowledge base at the same time. If users reject a rule, then the problem could not be completely solved using the existing rules so the artificial intelligence would then propose a new set of rules.

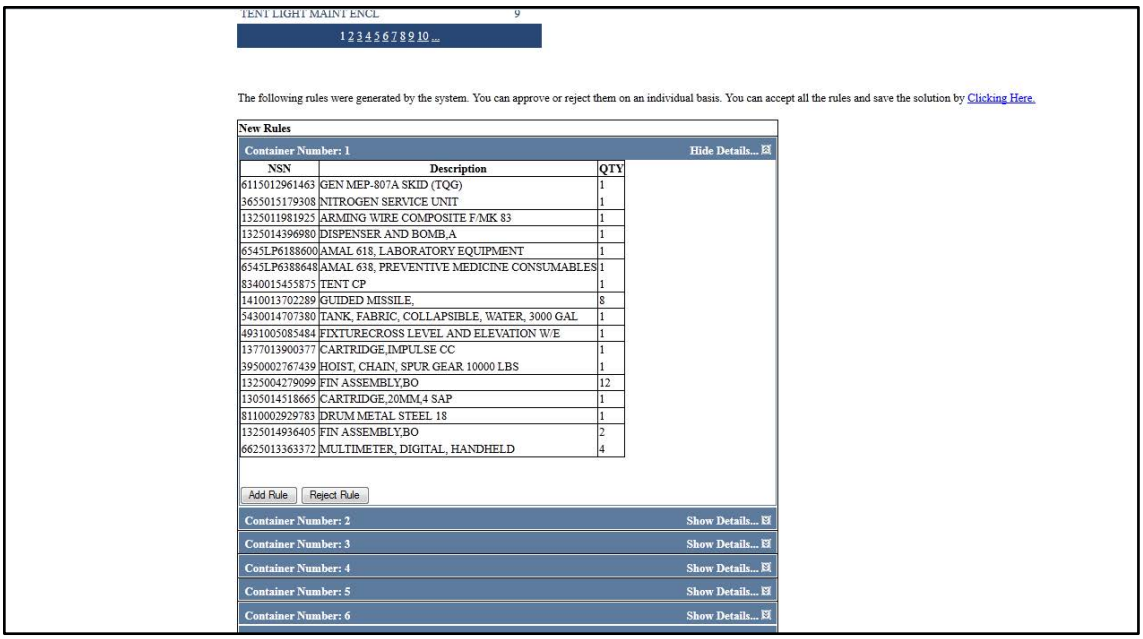
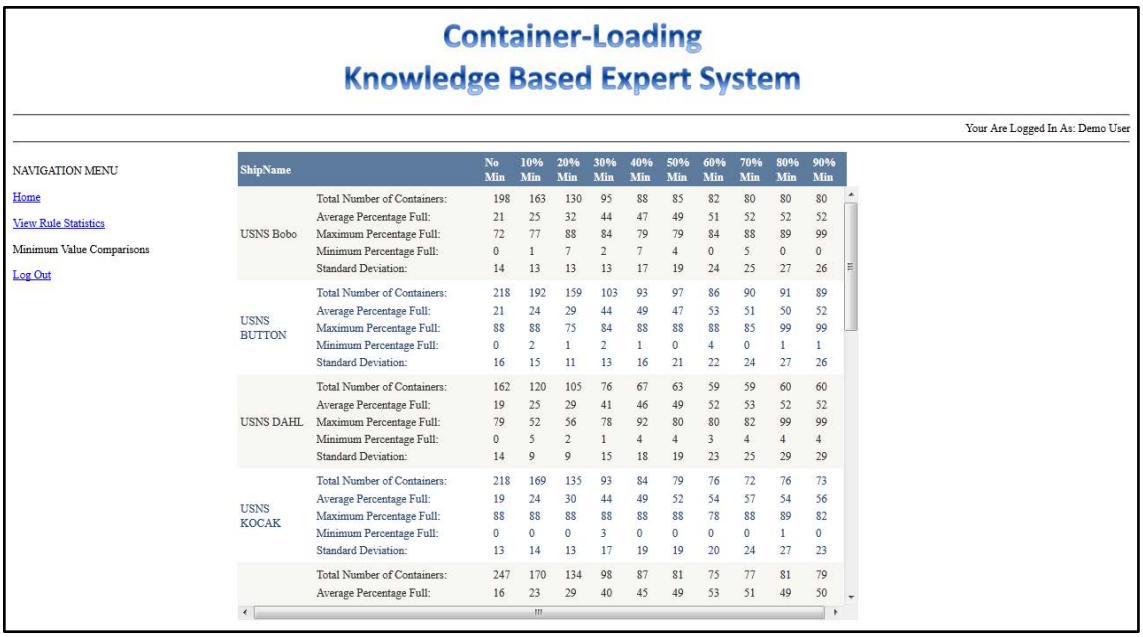


Figure 20: Adding Potential Rules from the Artificial Intelligence

Once all of the problems for each ship had been solved, the results needed to be extracted from the system in order to be analyzed. An interface was created in order to generate the statistics necessary to complete the analysis, as shown in Figure 21. For each ship, each problem was analyzed, and the total number of containers was totaled for each problem. The total number of containers loaded was used as the main metric for determining the level of optimization. The average percentage full of the containers from that problem was also calculated, which was used as a second optimization metric.



ShipName		No Min	10% Min	20% Min	30% Min	40% Min	50% Min	60% Min	70% Min	80% Min	90% Min
USNS Bobo	Total Number of Containers:	198	163	130	95	88	85	82	80	80	80
	Average Percentage Full:	21	25	32	44	47	49	51	52	52	52
	Maximum Percentage Full:	72	77	88	84	79	79	84	88	89	99
	Minimum Percentage Full:	0	1	7	2	7	4	0	5	0	0
	Standard Deviation:	14	13	13	13	17	19	24	25	27	26
USNS BUTTON	Total Number of Containers:	218	192	159	103	93	97	86	90	91	89
	Average Percentage Full:	21	24	29	44	49	47	53	51	50	52
	Maximum Percentage Full:	88	88	75	84	88	88	88	85	99	99
	Minimum Percentage Full:	0	2	1	2	1	0	4	0	1	1
	Standard Deviation:	16	15	11	13	16	21	22	24	27	26
USNS DAHL	Total Number of Containers:	162	120	105	76	67	63	59	59	60	60
	Average Percentage Full:	19	25	29	41	46	49	52	53	52	52
	Maximum Percentage Full:	79	52	56	78	92	80	80	82	99	99
	Minimum Percentage Full:	0	5	2	1	4	4	3	4	4	4
	Standard Deviation:	14	9	9	15	18	19	23	25	29	29
USNS KOCAK	Total Number of Containers:	218	169	135	93	84	79	76	72	76	73
	Average Percentage Full:	19	24	30	44	49	52	54	57	54	56
	Maximum Percentage Full:	88	88	88	88	88	88	78	88	89	82
	Minimum Percentage Full:	0	0	0	3	0	0	0	0	1	0
	Standard Deviation:	13	14	13	17	19	19	20	24	27	23
	Total Number of Containers:	247	170	134	98	87	81	75	77	81	79
	Average Percentage Full:	16	23	29	40	45	49	53	51	49	50

Figure 21: Results Analysis Page

Chapter 5

RESULTS ANALYSIS

This chapter will explain the results from comparing the container-loading knowledge-based expert system with the historical data representing the manual container-loading processes for thirteen ships loaded between 2008 and 2011. The first experiment that will be discussed is the control experiment where the capabilities of the artificial intelligence algorithm were tested against the historical data without using the inference engine. The next experiment discussed is how the long-term minimum percentage to be used by the inference engine when using historical data was determined. Finally, once the minimum percentage was identified, the capabilities of the container-loading knowledge-based expert system are compared to the historical data corresponding to the ships loaded between 2008 and 2011.

5.1 Artificial Intelligence Control Experiment

Before testing the capabilities of the container-loading knowledge-based expert system as a whole, the capabilities of the artificial intelligence were tested. The results discussed in this section provided the baseline to see whether using historical data provides added benefit in later sections. The user interface, as described in section 4.10, in which problems are created allows for a problem to be solved exclusively using the artificial intelligence. A problem was created for each of the thirteen ships for which historical data was collected. Each problem represented the items that were loaded in the past aboard each ship.

The container-loading knowledge-based expert system solved each problem. Figure 22 displays the raw data from the results of the artificial intelligence control experiment. The historical data container count represents how many containers it took the container loading experts to load all the equipment and supplies for each ship. The artificial intelligence container count represents how many containers were needed for the artificial intelligence to load the same number of equipment and supplies. The percent decrease column shows the percent decreased by using the artificial intelligence for each ship and is averaged at the bottom. The results show that the artificial intelligence can function effectively in the problem domain because for each ship tested the artificial intelligence was able to load the gear in fewer containers than the container-loading experts. Using only the artificial intelligence, the container-loading knowledge-based expert system loaded all the items for each ship into an average of 45.9% fewer containers than the container-loading experts did manually. Figure 23 displays the data from Figure 22 graphically, showing that the total container count for the artificial intelligence was always lower than the results from the container-loading experts.

Ship Name	Historical Data Container Count	Artificial Intelligence Container Count	Percentage Decrease
Ship 1	151	80	47.0%
Ship 2	171	90	47.4%
Ship 3	108	59	45.4%
Ship 4	158	73	53.8%
Ship 5	134	79	41.0%
Ship 6	150	108	28.0%
Ship 7	61	34	44.3%
Ship 8	174	92	47.1%
Ship 9	172	75	56.4%
Ship 10	74	32	56.8%
Ship 11	75	38	49.3%
Ship 12	115	73	36.5%
Ship 13	125	71	43.2%
AVERAGE	128.3	69.5	45.9%

Figure 22: Artificial Intelligence Control Experiment Results

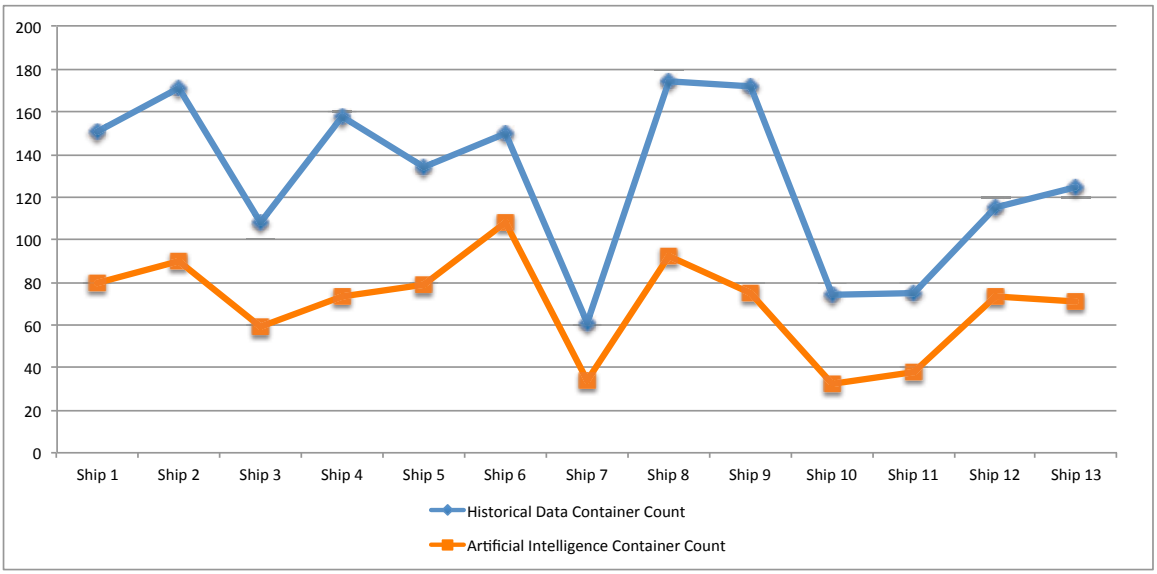


Figure 23: Artificial Intelligence Control Experiment Results Chart

In addition to reducing the number of containers, the average percentage full of each container also increased. The historical data column in Figure 24 shows the average percentage full of the containers loaded onto each ship by the container-loading experts.

The artificial intelligence column shows how full the average container loaded by the artificial intelligence was for the experiment. The averages, shown at the bottom of Figure 24, show that the historical data from the container-loading experts had the average container 27.4% full as opposed to 51.5% by the artificial intelligence. Figure 25 shows the data from Figure 24 graphically in which the line representing the results from the artificial intelligence is always above the line representing the container-loading experts. This metric was chosen because the higher the average percentage full the containers are for a particular ship, the fewer overall containers it will take to load all of the equipment and supplies. The artificial intelligence control experiment illustrates that the artificial intelligence can load containers more compactly than the container-loading experts resulting in the same set of equipment and supplies in fewer containers.

Ship Name	Historical Data	Artificial Intelligence
Ship 1	27%	52%
Ship 2	27%	51%
Ship 3	28%	53%
Ship 4	26%	56%
Ship 5	29%	50%
Ship 6	34%	48%
Ship 7	27%	48%
Ship 8	29%	55%
Ship 9	25%	58%
Ship 10	25%	58%
Ship 11	23%	45%
Ship 12	27%	44%
Ship 13	29%	51%
Average	27.4%	51.5%

Figure 24: Artificial Intelligence Control Experiment Percentage Full Statistics

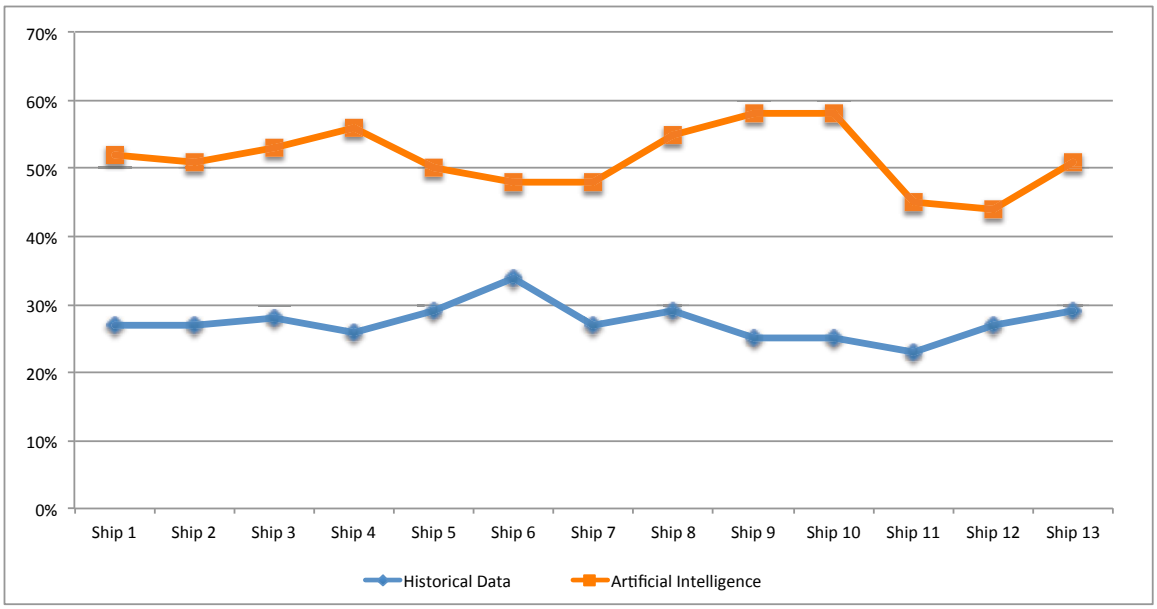


Figure 25: Artificial Intelligence Control Experiment Percentage Graph

5.2 Inference Engine Minimum Percentage Experiment

The next experiment conducted was to determine what the minimum percentage should be for the inference engine when using historical data. The user interface, where problems are created, was also configured to allow for any minimum value to be used for testing purposes. For each of the thirteen ships, ten problems were created each with a different minimum percentage starting at no minimum percentage and increasing by ten percent up to ninety percent. Each problem was solved using the container-loading knowledge-based expert system. In this experiment, the full capabilities of the system were tested. The inference engine used historical data that was above the minimum percentage until there were no rules left that could be applied. The artificial intelligence then solved the rest of the problem.

The resulting container counts for each problem are shown in Figure 26. Each ship's data was loaded using the ten different minimum values represented by the column headers.

The number in the chart represents the number of containers it took the container-loading knowledge-based expert system to load all the equipment and supplies for that ship. The results in their raw form cannot be compared across different ships because each ship had a different number of equipment and supplies loaded. Therefore, for each problem the minimum container count across all ten problems was identified for each ship, shown as the absolute minimum column of Figure 26. Each container count was then divided by the absolute minimum value for that ship resulting in the percentage of the minimum container count each total represents, shown in Figure 27. Now each total represents the percentage of the minimum container count and the percentages can be compared across different ships.

Ship Name	No Min	10% Min	20% Min	30% Min	40% Min	50% Min	60% Min	70% Min	80% Min	90% Min		Absolute Min
Ship 1	198	163	130	95	88	85	82	80	80	80		80
Ship 2	218	192	159	103	93	97	86	90	91	89		86
Ship 3	162	120	105	76	67	63	59	59	60	60		59
Ship 4	218	169	135	93	84	79	76	72	76	73		72
Ship 5	247	170	134	98	87	81	75	77	81	79		75
Ship 6	278	234	176	134	111	106	108	108	107	107		106
Ship 7	102	85	58	42	38	35	35	32	34	35		32
Ship 8	248	188	155	115	97	94	86	85	89	89		85
Ship 9	214	183	148	101	88	83	76	70	78	75		70
Ship 10	128	74	56	44	34	33	33	32	31	31		31
Ship 11	92	74	52	45	38	37	35	37	39	38		35
Ship 12	212	137	110	82	77	74	70	70	73	72		70
Ship 13	196	155	119	89	80	74	69	70	71	69		69

Figure 26: Container Counts for Minimum Percentage Experiment

Ship Name	No Min	10% Min	20% Min	30% Min	40% Min	50% Min	60% Min	70% Min	80% Min	90% Min
Ship 1	247.5%	203.8%	162.5%	118.8%	110.0%	106.3%	102.5%	100.0%	100.0%	100.0%
Ship 2	253.5%	223.3%	184.9%	119.8%	108.1%	112.8%	100.0%	104.7%	105.8%	103.5%
Ship 3	274.6%	203.4%	178.0%	128.8%	113.6%	106.8%	100.0%	100.0%	101.7%	101.7%
Ship 4	302.8%	234.7%	187.5%	129.2%	116.7%	109.7%	105.6%	100.0%	105.6%	101.4%
Ship 5	329.3%	226.7%	178.7%	130.7%	116.0%	108.0%	100.0%	102.7%	108.0%	105.3%
Ship 6	262.3%	220.8%	166.0%	126.4%	104.7%	100.0%	101.9%	101.9%	100.9%	100.9%
Ship 7	318.8%	265.6%	181.3%	131.3%	118.8%	109.4%	109.4%	100.0%	106.3%	109.4%
Ship 8	291.8%	221.2%	182.4%	135.3%	114.1%	110.6%	101.2%	100.0%	104.7%	104.7%
Ship 9	305.7%	261.4%	211.4%	144.3%	125.7%	118.6%	108.6%	100.0%	111.4%	107.1%
Ship 10	412.9%	238.7%	180.6%	141.9%	109.7%	106.5%	106.5%	103.2%	100.0%	100.0%
Ship 11	262.9%	211.4%	148.6%	128.6%	108.6%	105.7%	100.0%	105.7%	111.4%	108.6%
Ship 12	302.9%	195.7%	157.1%	117.1%	110.0%	105.7%	100.0%	100.0%	104.3%	102.9%
Ship 13	284.1%	224.6%	172.5%	129.0%	115.9%	107.2%	100.0%	101.4%	102.9%	100.0%
Average	296.1%	225.5%	176.3%	129.3%	113.2%	108.2%	102.7%	101.5%	104.8%	103.5%

Figure 27: Percentages of the Absolute Minimum Values

The percentages in Figure 27 that represent the absolute minimum container count for each ship are those cells with one hundred percent. Any cell with a number greater than one hundred percent represents a total that was greater than the absolute minimum for that particular ship by the percentage in the cell. Figure 28 shows the data from Figure 27 in a graphical form in which the values decrease rapidly after the thirty percent minimum threshold and reaches its minimum at the seventy percent minimum threshold. Figure 29 graphs the averages for each minimum percentage, represented in the bottom row of Figure 27, and provides a much clearer representation of the performance.

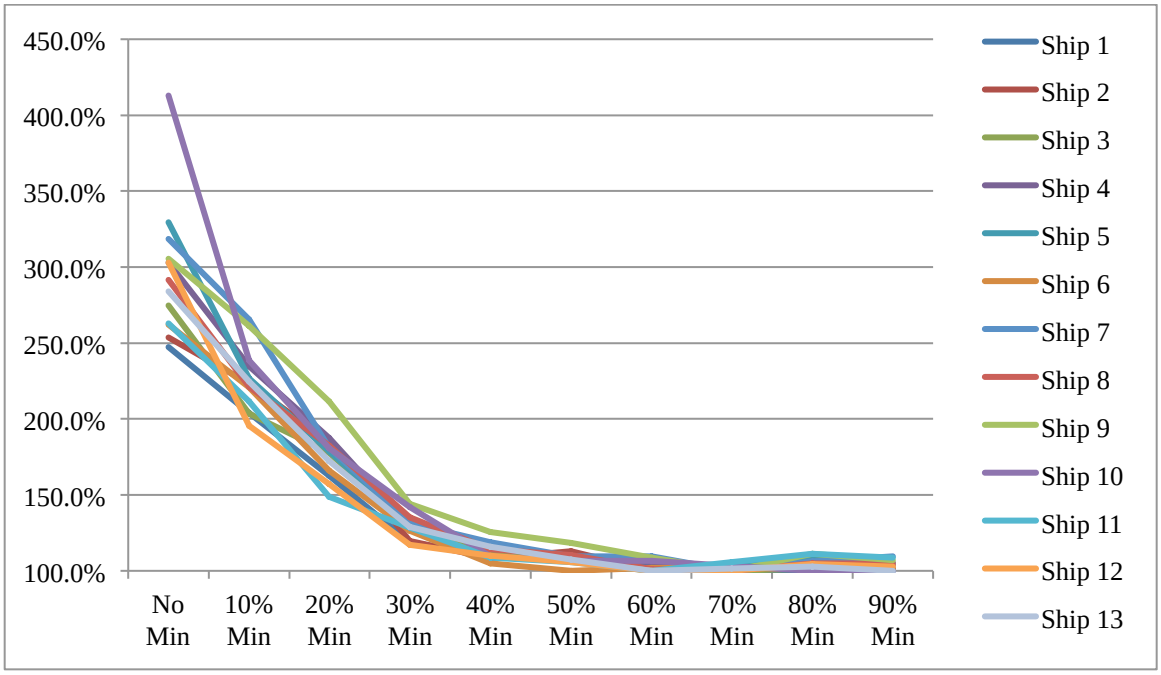


Figure 28: Graphical Percentages of the Absolute Minimum Values

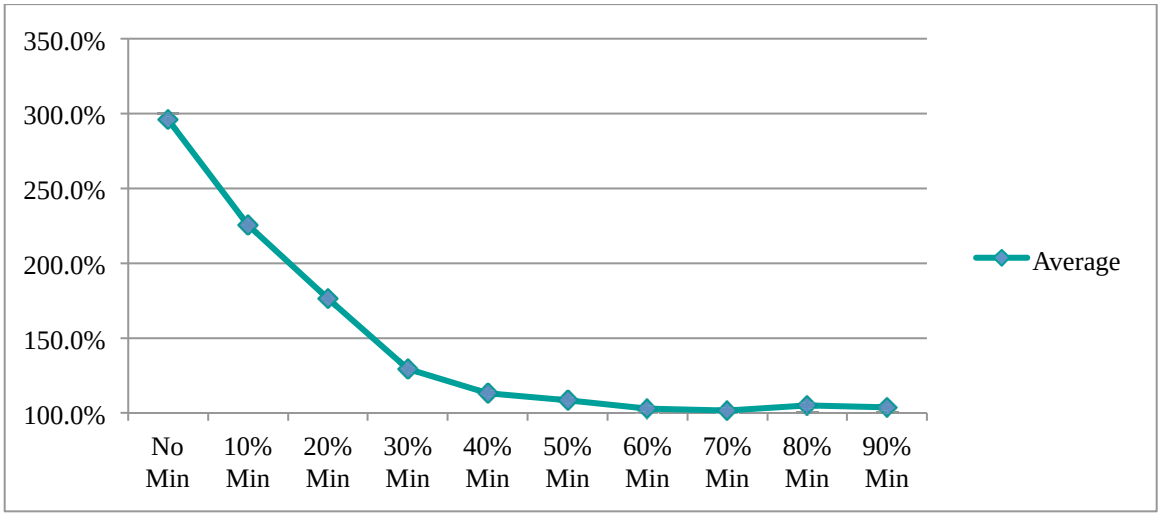


Figure 29: Graph of Average Percentages of the Absolute Minimum

The lowest average value for the minimum value threshold for historical data is at seventy percent. These results imply that the minimum values created by the system are most often occurring with a minimum percentage of seventy percent for historical data.

Seventy percent is where the optimal combination between the historical data and the artificial intelligence exists. The artificial intelligence, as shown above in Figure 24, has an average value of 51.5%. Therefore, when the minimum value is set at seventy percent there are enough historical data rules used to increase the overall percentage full of the containers before the artificial intelligence solves the rest of the problem. Increasing the overall percentage full of each container leads to a lower container count. The problems solved with minimum values above seventy percent did not have as many rules that could be used from historical data and thus the artificial intelligence had to solve more of the problem. Since the artificial intelligence averages loading containers 51.5% full, the more of the problem the artificial intelligence had to solve the more the average percentage full of the containers approached 51.5%. The improved methodology relies on data warehousing to provide the ability to exceed the capabilities of the artificial intelligence alone. The effectiveness of the data warehouse is minimized when the minimum percentage for the inference engine is higher than seventy percent.

Figure 30 shows the average percentage full containers loaded for each problem solved were. The problem corresponding to each ship was solved ten different times each with a different minimum value and thus generated ten different percentages. The percentages at sixty, seventy, and ninety percentages are all above the 51.5% average, as shown in Figure 24, for the artificial intelligence by itself. Figure 31 graphically represents the data from Figure 30. The percentage full peaks at seventy percent and thus explains why seventy percent had the lowest container counts. Figure 32, which graphs the average of all the percentages for each minimum value, shows similar results. The containers loaded using seventy percent as the minimum value for historical data had the highest average

percentage full. Therefore, empirical data from this experiment, including both the container counts and the average percentage full of containers, shows that the long term minimum percentage that should be used for historical data is seventy percent.

Ship Name	No Min	10% Min	20% Min	30% Min	40% Min	50% Min	60% Min	70% Min	80% Min	90% Min
Ship 1	21%	25%	32%	44%	47%	49%	51%	52%	52%	52%
Ship 2	21%	24%	29%	44%	49%	47%	53%	51%	50%	52%
Ship 3	19%	25%	29%	41%	46%	49%	52%	53%	52%	52%
Ship 4	19%	24%	30%	44%	49%	52%	54%	57%	54%	56%
Ship 5	16%	23%	29%	40%	45%	49%	53%	51%	49%	50%
Ship 6	18%	22%	29%	38%	47%	49%	48%	48%	48%	48%
Ship 7	16%	19%	28%	39%	43%	47%	47%	51%	48%	47%
Ship 8	20%	26%	32%	43%	52%	53%	58%	59%	56%	56%
Ship 9	20%	24%	29%	43%	50%	53%	58%	63%	56%	58%
Ship 10	14%	25%	33%	42%	55%	56%	56%	58%	60%	60%
Ship 11	18%	23%	33%	38%	45%	47%	49%	47%	44%	45%
Ship 12	15%	23%	29%	39%	41%	43%	45%	45%	43%	44%
Ship 13	18%	23%	30%	41%	45%	49%	53%	52%	51%	53%
Average	18.1%	23.5%	30.2%	41.2%	47.2%	49.5%	52.1%	52.8%	51.0%	51.8%

Figure 30: Average Percentage Full of Containers

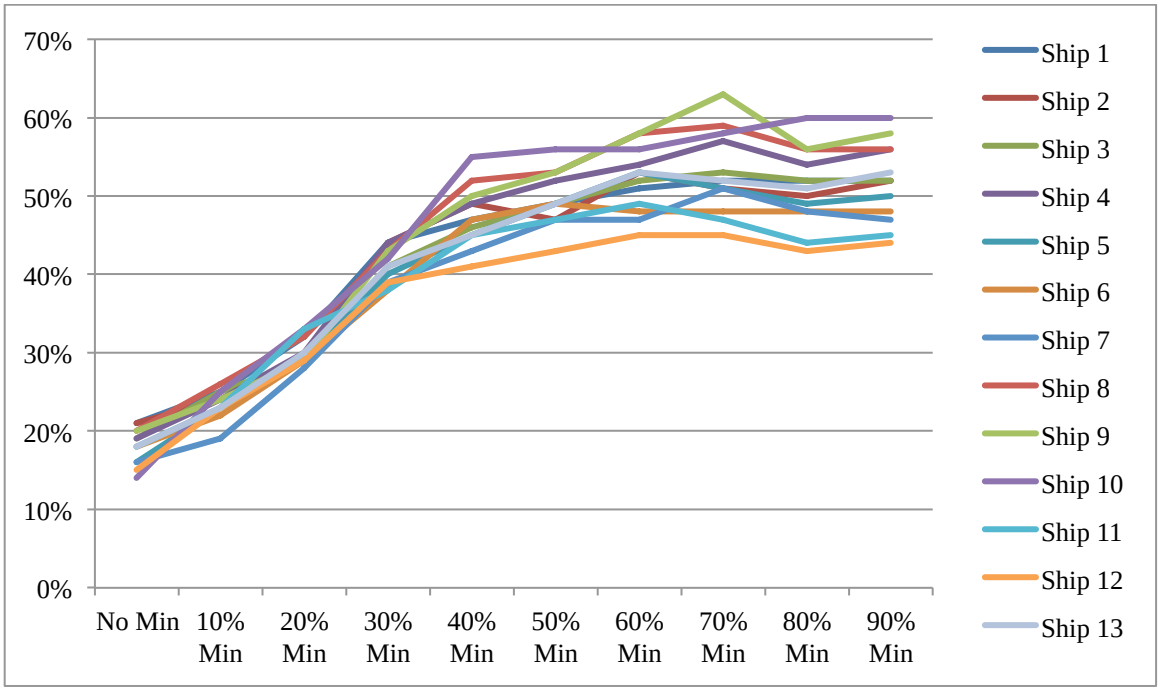


Figure 31: Graph of Percentage Full of Containers

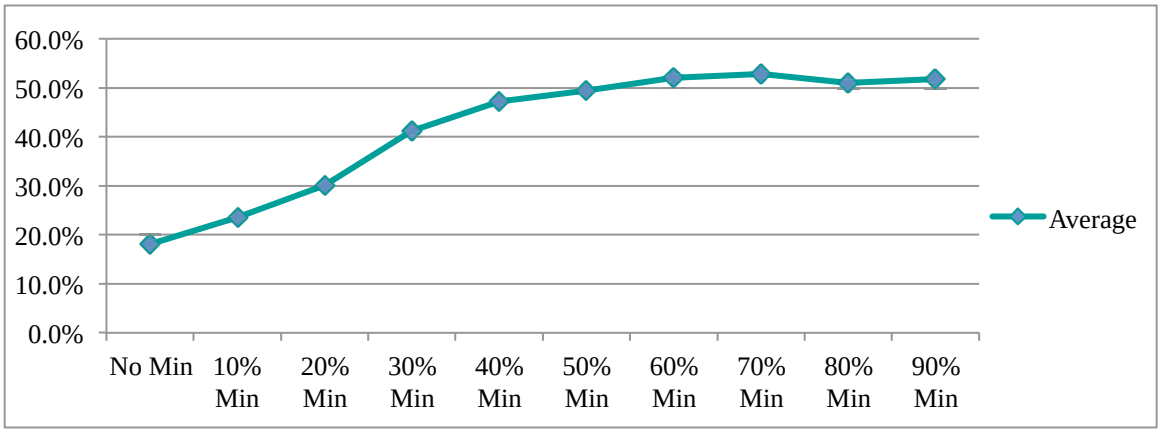


Figure 32: Averages of Percentage Full of Containers

5.3 Final Comparison

Once the capabilities of the artificial intelligence were identified and the optimal minimum percentage to use for historical data was identified, the final comparison could be conducted. The results from the tests with the minimum percentage of seventy percent were compared to the historical data and against the artificial intelligence by itself. The historical data container count was always higher than the container count for the improved methodology, seen by comparing the historical data container count with the improved methodology container count column in Figure 33. The improved methodology performance, as shown in Figure 33 by the average percentage decrease for the improved methodology, decreased the overall container counts needed to load each ship by a greater margin than by strictly using the artificial intelligence. Therefore by combining both historical data and artificial intelligence, a more optimal solution, meaning loading the same number of equipment and supplies into a smaller number of containers, was achieved in each case by the improved methodology. Figure 34 graphs these results showing how the total container count for the improved methodology is

always below the historical data container count and always below or equal to the artificial intelligence container count.

Ship Name	Historical Data Container Count	Artificial Intelligence Container Count	Percentage Decrease (Artificial Intelligence vs Historical Data)	Improved Methodology Container Count (70% Minimum Value)	Percentage Decrese (Improved Methodology vs Historical Data)
Ship 1	151	80	47.0%	80	47.0%
Ship 2	171	90	47.4%	90	47.4%
Ship 3	108	59	45.4%	59	45.4%
Ship 4	158	73	53.8%	72	54.4%
Ship 5	134	79	41.0%	77	42.5%
Ship 6	150	108	28.0%	108	28.0%
Ship 7	61	34	44.3%	32	47.5%
Ship 8	174	92	47.1%	85	51.1%
Ship 9	172	75	56.4%	70	59.3%
Ship 10	74	32	56.8%	32	56.8%
Ship 11	75	38	49.3%	37	50.7%
Ship 12	115	73	36.5%	70	39.1%
Ship 13	125	71	43.2%	70	44.0%
Average	128.3	69.5	45.9%	67.8	47.2%

Figure 33: Final Comparison Statistics

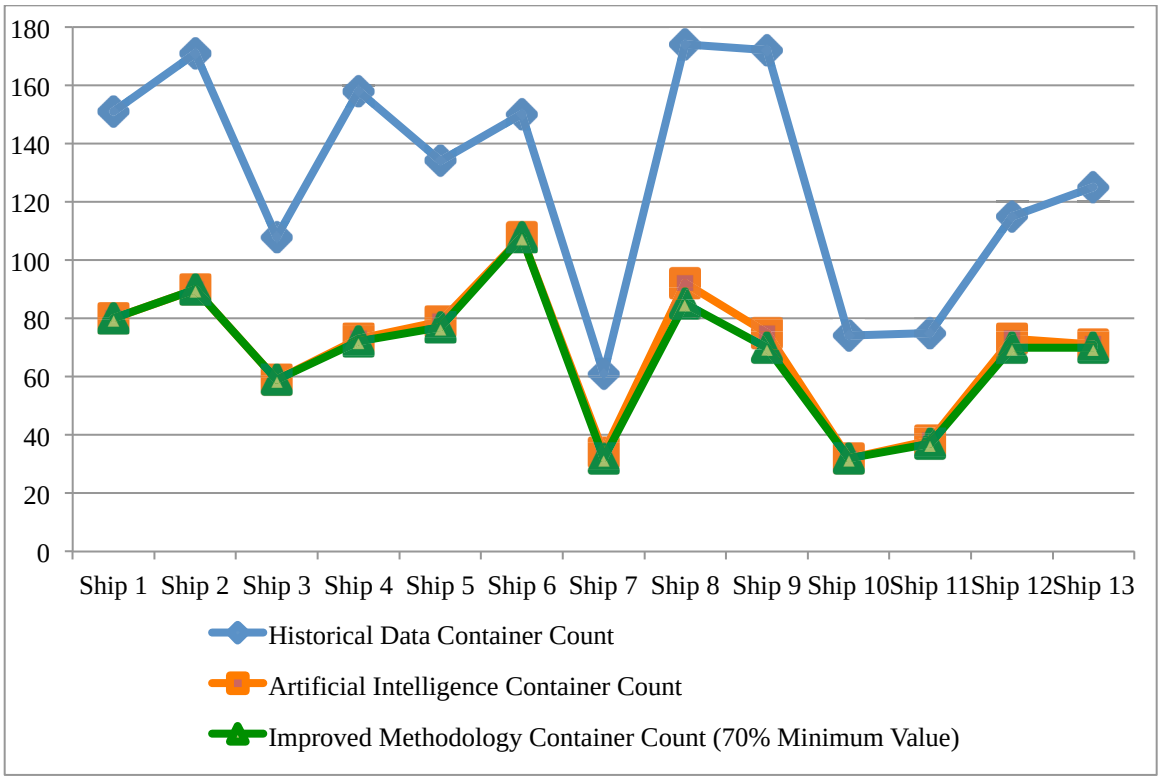


Figure 34: Final Comparison Graph

The average percentage full of containers for each problem supports the same conclusions. As shown in Figure 35, the average percentage full of each container is as high or higher for each ship in the improved methodology as compared to both the historical data and the artificial intelligence. The higher the average percentage full for each container, the lower the overall container count will be. The average container from historical data was 27.4% full, as shown in Figure 35. The average container from the artificial intelligence control experiment was 51.5% full, which is a percentage increase of 89.2%, as shown in Figure 35. The average container from using the container-loading knowledge-based expert system with a minimum percentage of seventy percent for historical data was 52.8% full, which was a percentage increase of 94.9%, also shown in Figure 35. Figure 36 graphically represents the data from Figure 35. The line corresponding to the improved methodology is always as high or higher than the artificial intelligence and always higher than the historical data.

The artificial intelligence experiment led to a 45.9% reduction in the container count, as shown in Figure 33. However, by combining historical data and artificial intelligence, the container-loading knowledge-based expert system was able to reduce the container count by 47.2%, also shown in Figure 33. Corresponding results were found when analyzing the average percentage full containers were loaded by each method. The artificial intelligence led to an increase in the average percentage full of the containers loaded by 89.7%, as shown in Figure 35. However, the improved methodology led to an increase in the average percentage full of 94.9%, also shown in Figure 35. The improved methodology employed in the container-loading knowledge-based expert system

optimizes the balance between historical data and the capabilities of the artificial intelligence to produce an optimal solution.

Ship Name	Historical Data	Artificial Intelligence	Percentage Increase (Historical Data vs Artificial Intelligence)	Improved Methodology (70% Minimum Value)	Percentage Increase (Historical Data vs Improved Methodology)
Ship 1	27%	52%	92.6%	52%	92.6%
Ship 2	27%	51%	88.9%	51%	88.9%
Ship 3	28%	53%	89.3%	53%	89.3%
Ship 4	26%	56%	115.4%	57%	119.2%
Ship 5	29%	50%	72.4%	51%	75.9%
Ship 6	34%	48%	41.2%	48%	41.2%
Ship 7	27%	48%	77.8%	51%	88.9%
Ship 8	29%	55%	89.7%	59%	103.4%
Ship 9	25%	58%	132.0%	63%	152.0%
Ship 10	25%	58%	132.0%	58%	132.0%
Ship 11	23%	45%	95.7%	47%	104.3%
Ship 12	27%	44%	63.0%	45%	66.7%
Ship 13	29%	51%	75.9%	52%	79.3%
Average	27.4%	51.5%	89.7%	52.8%	94.9%

Figure 35: Average Percentage Full Final Statistics

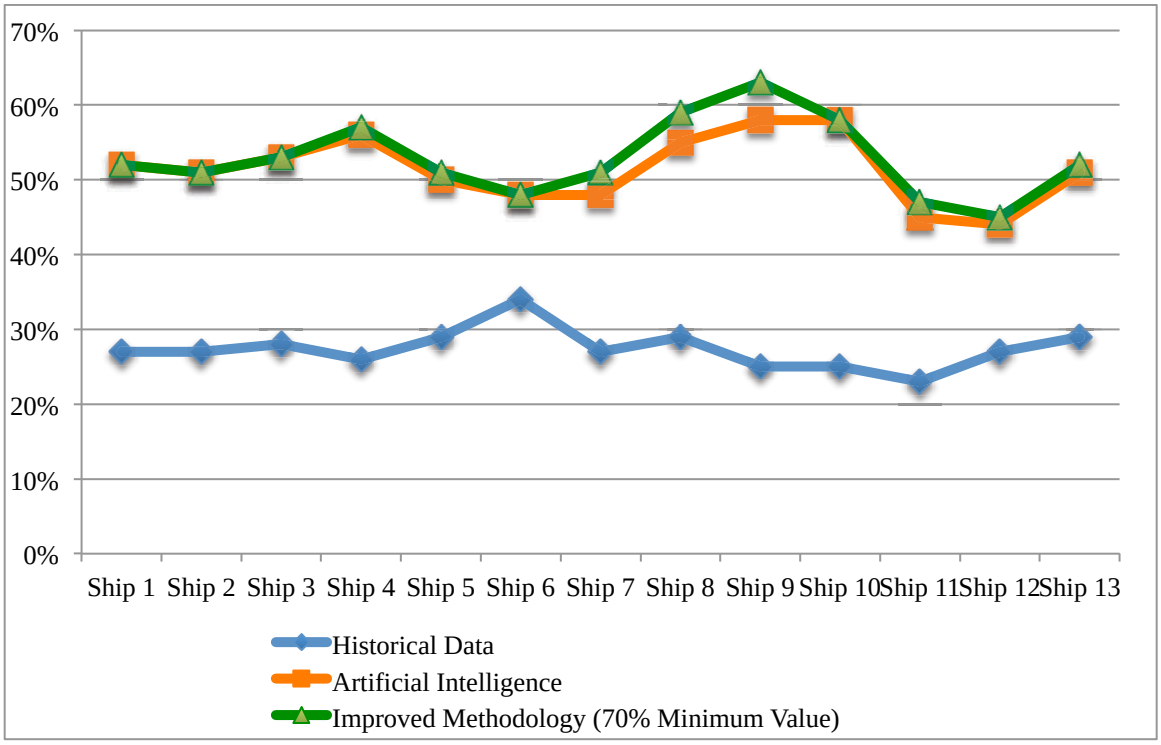


Figure 36: Average Percentage Full Final Graph

Chapter 6

CONCLUSIONS AND FUTURE WORK

In this chapter, conclusions based on the results of the previous chapter will be discussed in section 6.1. Discussions about future work will be discussed in section 6.2.

6.1 Conclusions

Knowledge-based expert systems can drastically reduce the amount of time necessary to complete complex tasks in a particular domain when implemented properly. However, there are significant problems that can arise during the implementation of a knowledge-based expert system that can prevent the system from ever becoming functional. Furthermore, the post implementation maintenance requirements of a knowledge-based expert system can be difficult and time consuming. Only by identifying and mitigating these risks can a knowledge-based expert system be successfully implemented and maintained.

An improved methodology for creating and maintaining knowledge-based expert systems was introduced in this thesis. The improved methodology streamlines the knowledge acquisition process by mining historical data to augment the interviews conducted by the knowledge engineer. The historical data provide a strong starting point for the knowledge base, which is transformed into a data warehouse to provide the inference engine fast access to the historical data. Furthermore, artificial intelligence is incorporated into the knowledge-based expert system in order to suggest new rules that can be added to the knowledge base. The suggested rules will allow the knowledge-

based expert system to completely solve problems that cannot be solved given the information contained within the knowledge base. The incorporation of the artificial intelligence removes the need for a manual knowledge acquisition module and thus reduces the resource requirements for maintaining the knowledge-based expert system after its initial implementation.

The improved methodology was tested by creating a knowledge-based expert system for a container-loading process. Container-loading experts were interviewed to discuss their processes. The transportation system where the data was recorded by the container-loading experts was mined for the historical data from thirteen ships loaded between 2008 and 2011. A data warehouse was created to serve as the knowledge base to store historical data. The inference engine was created in order to pass partially completed solutions to the artificial intelligence. The artificial intelligence then constructed the rules that needed to be added to the knowledge base in order to complete the solution.

In order to test the container-loading knowledge-based expert system, several experiments were conducted. The first experiment tested the capabilities of the artificial intelligence algorithm. The historical data from each of the thirteen ships loaded by the container-loading experts between 2008 and 2011 were turned into distinct problems in the system. Each problem was then solved by the artificial intelligence without the use of the inference engine or any historical data. The artificial intelligence was able to load all the items from each ship with an average of 45.9% less containers than the container-loading experts had done in the past, as shown in Figure 27. The average percentage full the containers loaded by the artificial intelligence was 51.5% as opposed to 27.4% by the container-loading experts, as shown in Figure 29. This experiment provided a control

baseline for later experiments to test the impact of using both historical data and artificial intelligence.

The second experiment was designed to identify what the long-term minimum value should be for using historical data. Each rule stored in the knowledge base represents some percentage of a fully loaded container. The inference engine was created so that it would not use any rules below the minimum percentage set before the problem was solved. For each of the thirteen ships, ten problems were created each with a different minimum value starting with no minimum value and increasing by ten percent up to ninety percent. Each problem was then solved independently so the results could be compared. The results for the problems solved with a minimum value of seventy percent yielded the lowest container counts on average and also yielded the highest average percentage full for the containers loaded. Therefore, seventy percent was selected to be the long-term minimum value for the inference engine to use when selecting historical data.

The final experiment compared the results from the container-loading knowledge-based expert system using a minimum value of seventy percent with the results from the artificial intelligence control experiment and the historical results. The container-loading knowledge-based expert system was able to reduce the total number of containers needed to load the thirteen ships by 47.2%, which was a greater reduction than the artificial intelligence alone. Furthermore, the containers were on average 52.8% full, which was greater than the artificial intelligence alone and greater than the historical results from the container-loading experts. These results show that by utilizing both historical data and

artificial intelligence a more optimal solution can be created than by using either one of them independently.

The most important part of the improved methodology was to identify where the optimal combination of historical data and artificial intelligence existed. The testing phase of the improved methodology is thus critical to a successful implementation. If the optimal balance is achieved then the knowledge-based expert system can produce optimal solutions while reducing the maintenance requirements of the knowledge base.

6.2 Future Work

Future experiments with the improved methodology for the knowledge-based expert systems need to be conducted in other problem domains. Other areas within the shipping industry could also be analyzed, for example this methodology could be implemented to load a ship with vehicles. Also, the a knowledge-based expert system could be created to create load plans for ships and integrated with Wilson's algorithm, as described in Chapter 2 [Wilson99]. By using the improved methodology in other domains, a more defined process for establishing the bounds for the inference engine using historical data could be achieved.

The impact of historical data when coupled with artificial intelligence is an area that could be improved. Fine tuning the inference engine and possibly modifying the artificial intelligence could potentially allow the historical data to provide a more significant impact beyond the capabilities of the artificial intelligence alone. Given the amount of data that is now stored and archived by organizations, it is important to investigate improved ways of utilizing the data to improve productivity and quality.

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Appendix A

EXAMPLE OF USER INTERFACE SOURCE CODE

The user interfaces were created as web pages using Microsoft .Net framework 4.0. The source code for these web pages is split into two files. The first file with the extension ".aspx" is similar to a standard HTML file where the layout of the web page is defined. The second file with the extension ".aspx.vb" is where the code is created for specific events for the web page.

A.1 ViewSolutions.aspx

Description:

This file is where solutions can be created and viewed in the system. The web pages display the solutions using standard active server page (ASP) controls which when rendered to the client are transformed into standard HTML.

```
<%@ Page Title="" Language="vb" AutoEventWireup="false" MasterPageFile="~/SiteMaster.Master"
CodeBehind="ViewSolution.aspx.vb" Inherits="ExpertSystem.ViewSolution" %>
<%@ Register Assembly="AjaxControlToolkit" Namespace="AjaxControlToolkit" TagPrefix="asp" %>
…
<asp:Content ID="Content2" ContentPlaceHolderID="ContentPlaceHolder1" runat="server">
…
   <asp:GridView ID="gvSolution" runat="server" AutoGenerateColumns="False" >
      <Columns>
         <asp:TemplateField HeaderText="Solution Description">
            <ItemTemplate>
               <asp:Panel ID="pHeader" runat="server" cssclass="collapsePanelHeader">
                     <table width="100%" >
                           <tr>
                           <td style="text-align:left; width:80%">
                                          Container Number:
                                          <asp:Label ID="lblContainerNumber" runat="server"
                                          Text="Label"
                                          ondatabinding="lblContainer_DataBinding"></asp:Label>
                                          Rule ID:
                                          <asp:Label ID="lblRuleGuid" runat="server"
                                          Text="Label"></asp:Label
                                          Percentage Full:
                                          <asp:Label ID="lblPercentageFull" runat="server"
                                          Text="Label"></asp:Label>
                           </td>
                           <td style="text-align:right; width:20%">
                                          <asp:Label ID="lblHeader" runat="server"
                                          Text="Label"></asp:Label>
                                          <asp:Image ID="imgToggle" runat="server"
                                          ImageUrl="Images/collapse.jpg" />
```

```
                        </td>
                        </tr>
                    </table>
                </asp:Panel>
                <asp:Panel ID="pContent" runat="server" CssClass="collapsePanel">
                    <asp:GridView ID="gvChildItems" runat="server">
                    </asp:GridView>
                </asp:Panel>
                <asp:CollapsiblePanelExtender ID="CollapsiblePanelExtender1" runat="server"
                    CollapseControlID="pHeader" Enabled="True" ExpandControlID="pHeader"
                    TextLabelID="lblHeader" TargetControlID="pContent"
                    CollapsedImage="~/Images/expand.jpg" ExpandedImage="~/Images/collapse.jpg"
                    CollapsedText="Show Details..." ExpandedText="Hide Details..."
                    ImageControlID="imgToggle" Collapsed="True" >
                </asp:CollapsiblePanelExtender>
            </ItemTemplate>
        </asp:TemplateField>
    </Columns>
    <HeaderStyle HorizontalAlign="Left" />
</asp:GridView>
<br />
    …
</asp:Content>
```

A.2 ViewSolutions.aspx.vb

Description:

ViewSolutions.aspx.vb contains the code that is executed on the different events created by ViewSolutions.aspx. Also, calls to the business layer are initiated from this page. This class contains the code that calls the inference engine to start solving a problem and the artificial intelligence to complete the problem if necessary.

```
Imports System.Data.SqlClient

Partial Public Class ViewSolution
    Inherits System.Web.UI.Page
    Public MyInfEngine As InferenceEngine
    Public MyAICONT As ContainerLoadingAI
    Public MyPublicSolution As Solution
    Public mytype As String

    Protected Sub Page_Load(ByVal sender As Object, ByVal e As System.EventArgs) Handles Me.Load
        Try
            If Not IsPostBack Then
                Dim cnsql As SqlConnection = New
SqlConnection(System.Web.Configuration.WebConfigurationManager.ConnectionStrings("ES").ToString)
                cnsql.Open()

                Dim cmsql As New SqlCommand
                cmsql.Connection = cnsql
                cmsql.CommandType = CommandType.StoredProcedure
                cmsql.CommandText = "CheckSolutionExists"
```

```
            Dim myGUID As New Guid(Request.QueryString("id"))

            cmsql.Parameters.Add("@GUID", SqlDbType.UniqueIdentifier)
            cmsql.Parameters("@GUID").Value = myGUID
            Dim count As Integer = cmsql.ExecuteScalar
            If count = 1 Then
               LoadSolution()
               mytype = "Load"
            Else
               mytype = "Create"
               cmsql = New SqlCommand
               cmsql.Connection = cnsql
               cmsql.CommandType = CommandType.StoredProcedure
               cmsql.CommandText = "UseHistoricalData"

               cmsql.Parameters.Add("@ProblemId", SqlDbType.UniqueIdentifier)
               cmsql.Parameters("@ProblemId").Value = myGUID

               Dim UseHistoricalData As Boolean = cmsql.ExecuteScalar
               Dim problem As New Problem(Request.QueryString("id"))
               Dim rules As New RuleCollection(UseHistoricalData, problem.Min)
               Dim myinferenceEngine As New InferenceEngine(rules, problem, UseHistoricalData)
               Dim completeSoultion As Boolean = myinferenceEngine.CreateSolution

               MyInfEngine = myinferenceEngine
               gvSolution.DataSource = myinferenceEngine.GetContainerTablefromSolution
               gvSolution.DataBind()
               Session.Add("myinfeng", myinferenceEngine)

               If Not completeSoultion Then
                  gvUnspreadItems.DataSource = myinferenceEngine.GetUnspreadItemsTablefromSolution
                  gvUnspreadItems.DataBind()
                  lblUnspreadItems.Visible = True
                  bCreateRules.Visible = True
                  lblSolutionInfo.Text = "A Complete Solution could not be created using the existing rules.
The items remaining are shown below.  Additional rules can be generated automatically by clicking the
generate rules button"
                  lblSolutionInfo.Visible = True
               Else
                  bSave.Visible = True
                  lblSolutionInfo.Text = "A Complete Solution was generated using the existing rules.  The
data can be saved for future use by clicking the save button"
                  lblSolutionInfo.Visible = True
               End If
            End If
            cnsql.Close()
         End If

      Catch ex As Exception
            Throw New Exception(ex.toString)
      End Try
   End Sub
…
      Protected Sub bCreateRules_Click(ByVal sender As Object, ByVal e As EventArgs) Handles
bCreateRules.Click
```

```
        Try
            MyInfEngine = CType(Session("myinfeng"), InferenceEngine)
            Dim myAI As New ContainerLoadingAI(MyInfEngine.GetUnspreadItems)
            MyAICONT = myAI
            Dim test As Integer = myAI.UnspreadTotals
            myAI.GenerateRules()
            gvNewRules.DataSource = myAI.ReturnContainerInfoAsTable
            gvNewRules.DataBind()
            Session.Add("myAI", myAI)
            lblSaveAllRules.Visible = True
            lblRulesGenerationInfo.Visible = True
            bCreateRules.Visible = False
        Catch ex As Exception
            Throw New Exception(ex.toString)
        End Try
    End Sub
…
End Class
```

Appendix B

EXAMPLE OF BUSINESS LAYER SOURCE CODE

Descriptions:

The business layer was designed to hold all the logic for the system. The classes created in the business later were designed to represent the different major components of the system, including the inference engine and the artificial intelligence. A small example of the artificial intelligence is shown below.

```
Public Class ContainerLoadingAI
   Private myUnspreadItems As Collection
   Private myContainers As Collection
   Private myGroupedNSNlookup As Collection

   Public Sub New(ByVal UnspreadItems As Collection)
      myUnspreadItems = UnspreadItems
      myContainers = New Collection
      myGroupedNSNlookup = New Collection
   End Sub
…
   Public Sub GenerateRules()
      Dim myContainerCount As Integer = 0
      Dim itemsLoaded As Integer = 0
      Dim myGUID As New Guid

      Dim myContainer As Container
      Dim ItemHasBeenLoaded As Boolean = False
      Dim ruleUsedAgain As Boolean = False

      GroupUnspreadItems()
      While ItemsRemain()
         Dim itemloaded As Boolean = False
         ruleUsedAgain = False
         If Not ItemHasBeenLoaded Then
            If myContainerCount > 0 Then
               myContainers.Add(myContainer)
               Dim NSNmappings As New Collection
               While TryRuleAgain(myContainer, NSNmappings, itemsLoaded)

                  myContainerCount += 1
                  ruleUsedAgain = True
                  Dim NewContainer As New Container
                  NewContainer = myContainer.Copy()
                  NewContainer.UpdateItemsNSN(NSNmappings, myGroupedNSNlookup)
                  NewContainer.GetContainerNumber = myContainerCount
                  myContainers.Add(NewContainer)
                  NSNmappings.Clear()
```

```
                NSNmappings = New Collection
            End While
        End If

        myContainerCount += 1

        myGUID = Guid.NewGuid

        If Not ItemsRemain() Then
            Exit While
        End If
        myContainer = New Container(myContainerCount, myGUID.ToString, False)
        myContainer.SetDimensions(240, 96, 96)
    End If
    Dim bestItem As ThreeDimensional_Object
    Dim bestTotal As New AI_Calculation
    Dim cornercount As Integer = 1
    For Each currentCorner As Coordinate In myContainer.Corners
        If currentCorner.IsActive Then
            …
            For Each currentItem As Child In myUnspreadItems
                …
                If currentItem.QTY > 0 Then
                    'Check to see if the corner has a height > 0 and if item can be stacked
                    If (currentCorner.Z_Coordinate > 0 And currentItem.Stack) Or
currentCorner.Z_Coordinate = 0 Then

                        'Check Configuration 1
                        Dim testItem As New ThreeDimensional_Object(currentItem.Length,
currentItem.Width, currentItem.Height, currentItem.NSN, False)
                        testItem.SetCoordinateUsingMin(currentCorner)
                        If myContainer.ItemCanBeLoaded(testItem) Then
                            itemloaded = True
                            Dim currentCalculation As New AI_Calculation(myContainer, testItem)
                            If currentCalculation.IsGreater(bestTotal) Then
                                bestItem = testItem
                                bestTotal = currentCalculation
                            End If
                        End If
                        If currentItem.Rotate Then

                            'Check Configuration 2
                            testItem = New ThreeDimensional_Object(currentItem.Length, currentItem.Height,
currentItem.Width, currentItem.NSN, False)
                            testItem.SetCoordinateUsingMin(currentCorner)
                            If myContainer.ItemCanBeLoaded(testItem) Then
                                itemloaded = True
                                Dim currentCalculation As New AI_Calculation(myContainer, testItem)
                                If currentCalculation.IsGreater(bestTotal) Then
                                    bestItem = testItem
                                    bestTotal = currentCalculation
                                End If
                            End If
                            'Check Configuration 3
                            testItem = New ThreeDimensional_Object(currentItem.Height,
currentItem.Length, currentItem.Width, currentItem.NSN, False)
```

```
                        testItem.SetCoordinateUsingMin(currentCorner)
                        If myContainer.ItemCanBeLoaded(testItem) Then
                            itemloaded = True
                            Dim currentCalculation As New AI_Calculation(myContainer, testItem)
                            If currentCalculation.IsGreater(bestTotal) Then
                                bestItem = testItem
                                bestTotal = currentCalculation
                            End If
                        End If
                        'Check Configuration 4
                        testItem = New ThreeDimensional_Object(currentItem.Height, currentItem.Width,
currentItem.Length, currentItem.NSN, False)
                        testItem.SetCoordinateUsingMin(currentCorner)
                        If myContainer.ItemCanBeLoaded(testItem) Then
                            itemloaded = True
                            Dim currentCalculation As New AI_Calculation(myContainer, testItem)
                            If currentCalculation.IsGreater(bestTotal) Then
                                bestItem = testItem
                                bestTotal = currentCalculation
                            End If
                        End If
                        'Check Configuration 5
                        testItem = New ThreeDimensional_Object(currentItem.Width, currentItem.Length,
currentItem.Height, currentItem.NSN, False)
                        testItem.SetCoordinateUsingMin(currentCorner)
                        If myContainer.ItemCanBeLoaded(testItem) Then
                            itemloaded = True
                            Dim currentCalculation As New AI_Calculation(myContainer, testItem)
                            If currentCalculation.IsGreater(bestTotal) Then
                                bestItem = testItem
                                bestTotal = currentCalculation
                            End If
                        End If
                        'Check Configuration 6
                        testItem = New ThreeDimensional_Object(currentItem.Width, currentItem.Height,
currentItem.Length, currentItem.NSN, False)
                        testItem.SetCoordinateUsingMin(currentCorner)
                        If myContainer.ItemCanBeLoaded(testItem) Then
                            itemloaded = True
                            Dim currentCalculation As New AI_Calculation(myContainer, testItem)
                            If currentCalculation.IsGreater(bestTotal) Then
                                bestItem = testItem
                                bestTotal = currentCalculation
                            End If
                        End If
                    End If
                End If
            End If
        Next
    …
Next
'if an item has been selected, load it
If bestTotal.HasBeenSet Then
    Dim newitemToAdd As New ThreeDimensional_Object
    newitemToAdd = SelectGroupedItem(bestItem)
    myContainer.Load3DChild(newitemToAdd)
```

```
                …
                ItemHasBeenLoaded = True
            Else
                ItemHasBeenLoaded = False
            End If
        End While

        If ItemHasBeenLoaded And Not ruleUsedAgain Then
            myContainers.Add(myContainer)
        End If
    End Sub
…
End Class
```

Appendix C

EXAMPLE OF DATA ACCESS LAYER SOURCE CODE

Description:

The code in the data access layer was designed to interact with the database and data warehouse through stored procedures. The objects created by the classes in the data access layer were designed to facilitate logical separations between objects within the database and data warehouse.

```
Imports System.Data.SqlClient
Imports System.Data

Public Class Container
   Private containerID As Integer
   Private childItems As Collection
   Private ruleID As String
   Private mylength_X As Integer
   Private mywidth_Y As Integer
   Private myheight_Z As Integer
   Private myCorners As Collection
   Private mynewRuleID As Integer
   Private isCopy As Boolean
   Private myTotalVolume As Integer
   …
   Public Sub Load3DChild(ByVal child As ThreeDimensional_Object)
      Dim newCoord As Coordinate
      Dim objectCorner As Coordinate = child.MinCoordinate
      childItems.Add(child)

      'remove the corner used to store this child
      For i As Integer = 1 To myCorners.Count
         Dim mycorner As Coordinate = CType(myCorners(i), Coordinate)
         If mycorner.IsEqual(child.MinCoordinate) Then
            myCorners.Remove(i)
            Exit For
         End If
      Next

      'add the seven new corners for the new object
      newCoord = New Coordinate(objectCorner.X_Coordinate + child.Length,
objectCorner.Y_Coordinate, objectCorner.Z_Coordinate)
      myCorners.Add(newCoord)

      newCoord = New Coordinate(objectCorner.X_Coordinate + child.Length, objectCorner.Y_Coordinate
+ child.Width, objectCorner.Z_Coordinate)
      myCorners.Add(newCoord)
```

```
        newCoord = New Coordinate(objectCorner.X_Coordinate + child.Length, objectCorner.Y_Coordinate
+ child.Width, objectCorner.Z_Coordinate + child.Height)
        myCorners.Add(newCoord)

        newCoord = New Coordinate(objectCorner.X_Coordinate + child.Length,
objectCorner.Y_Coordinate, objectCorner.Z_Coordinate + child.Height)
        myCorners.Add(newCoord)

        newCoord = New Coordinate(objectCorner.X_Coordinate, objectCorner.Y_Coordinate + child.Width,
objectCorner.Z_Coordinate)
        myCorners.Add(newCoord)

        newCoord = New Coordinate(objectCorner.X_Coordinate, objectCorner.Y_Coordinate + child.Width,
objectCorner.Z_Coordinate + child.Height)
        myCorners.Add(newCoord)

        newCoord = New Coordinate(objectCorner.X_Coordinate, objectCorner.Y_Coordinate,
objectCorner.Z_Coordinate + child.Height)
        myCorners.Add(newCoord)

        updateCorners()

    End Sub
    …
    Public Sub SaveContainer()
        Dim mydt As DataTable = Me.GetContainerDetailAsTable
        Dim cnsql As New
SqlConnection(System.Web.Configuration.WebConfigurationManager.ConnectionStrings("ES").ToString)
        cnsql.Open()
        Dim myGUID As New Guid(ruleID)
        Try
            Dim cmSQL As New SqlCommand
            For Each myrow As DataRow In mydt.Rows
                cmSQL = New SqlCommand
                cmSQL.CommandType = CommandType.StoredProcedure
                cmSQL.CommandText = "InsertRule"
                cmSQL.Connection = cnsql

                cmSQL.Parameters.Add("@GUID", SqlDbType.UniqueIdentifier)
                cmSQL.Parameters("@GUID").Value = myGUID

                cmSQL.Parameters.Add("@NSN", SqlDbType.Char)
                cmSQL.Parameters("@NSN").Value = myrow("NSN")

                cmSQL.Parameters.Add("@QTY", SqlDbType.Int)
                cmSQL.Parameters("@QTY").Value = CInt(myrow("QTY"))


                cmSQL.Parameters.Add("@UserName", SqlDbType.VarChar)
                cmSQL.Parameters("@UserName").Value = HttpContext.Current.User.Identity.Name.ToString

                cmSQL.ExecuteNonQuery()
            Next
            cmsql = New SqlCommand
            cmSQL.CommandType = CommandType.StoredProcedure
            cmSQL.CommandText = "UpdateVolume"
```

```
            cmSQL.Connection = cnsql

            cmSQL.Parameters.Add("@GUID", SqlDbType.UniqueIdentifier)
            cmSQL.Parameters("@GUID").Value = myGUID

            cmSQL.ExecuteNonQuery()
        Catch ex As Exception
            Throw New Exception(ex.toString)
        Finally
            cnsql.Close()
        End Try

    End Sub
    …
End Class
```

Appendix D

EXAMPLE OF STORED PROCEDURES

Description:

Stored procedures were used for all database and data warehouse queries. Below are examples of stored procedures that were called by the data access layer.

```
-- =============================================
-- Author: Lucien Millette
-- Create date: 8Dec2010
-- Description:     Inserts a new problem with inputted parameters
-- =============================================
CREATE PROCEDURE [dbo].[InsertProblem]
-- Input Parameters
@Name varchar(50),
@UseHistoricalData bit,
@MinimumPercentage int
AS
BEGIN
          -- SET NOCOUNT ON added to prevent extra result sets from
          -- interfering with SELECT statements.
          SET NOCOUNT ON;

   INSERT INTO [ProblemInfo]
        ([GUID]
        ,[Name]
        ,[CreatedOn]
        ,[UseHistoricalData]
        ,[MinimumPercentage])
    VALUES
        (NEWID()
        ,@Name
        ,CURRENT_TIMESTAMP
        ,@UseHistoricalData
        ,@MinimumPercentage)
END

-- =============================================
-- Author: Lucien Millette
-- Create date: 7Jan2011
-- Description: Inserts a part of a rule created by the AI
-- =============================================
CREATE PROCEDURE [dbo].[InsertRule]
-- Input Parameters
@GUID uniqueidentifier,
@NSN char(13),
@QTY int,
@UserName varchar(30)
```

```
AS
BEGIN
	-- SET NOCOUNT ON added to prevent extra result sets from
	SET NOCOUNT ON;

	Declare @ID integer;
	Declare @CurrentTime datetime;
	Declare @Minute int;
	Declare @Hour int;
	Declare @Day int;
	Declare @Month int;
	Declare @Year int;

	Select @CurrentTime = CURRENT_TIMESTAMP

	if not exists (select Time_ID from TimeDimension where Time_ID = @CurrentTime)
	Begin
		insert into TimeDimension values (
			@CurrentTime,
			DatePart(MINUTE, current_timestamp),
			DatePart(HOUR, current_timestamp),
			DatePart(DAY, current_timestamp),
			DatePart(Month, current_timestamp),
			DatePart(YEAR, current_timestamp))
	End

	if exists (Select * from RuleFactTable where GUID = @GUID)
		BEGIN
			select @ID = Rule_ID from RuleFactTable where GUID = @GUID
		END
	else
		BEGIN
			select @ID = MAX(Rule_ID) from RuleFactTable;
			set @ID = @ID +1;
		END
	if not exists (Select Rule_ID from RuleDimension where Rule_ID = @GUID)
		BEGIN
			insert into  RuleDimension (
					[Rule_ID],
					[Description],
					[RuleNumber])
					values (
					@GUID,
					'Added by ' + @UserName + ' via the AI',
					@ID)
		end
	INSERT INTO RuleFactTable

   VALUES
      (@GUID
      ,@NSN
      ,@CurrentTime
      ,@UserName
      ,@ID
      ,@QTY)
END
```

Appendix E

DATABASE AND DATA WAREHOUSE SQL

Description:

The SQL commands in this appendix were used to create the structures in the database and data warehouse that enabled the system to function.

```
/******  Data Warehouse SQL ******/

CREATE TABLE [dbo].[RuleDimension](
	[Rule_ID] [uniqueidentifier] NOT NULL,
	[Description] [varchar](50) NOT NULL,
	[RuleNumber] [int] NULL,
	[TotalVolume] [int] NULL,
 CONSTRAINT [PK_RuleDimension] PRIMARY KEY CLUSTERED
(
	[Rule_ID] ASC
)WITH (PAD_INDEX  = OFF, STATISTICS_NORECOMPUTE  = OFF, IGNORE_DUP_KEY = OFF,
ALLOW_ROW_LOCKS  = ON, ALLOW_PAGE_LOCKS  = ON) ON [PRIMARY]
)

CREATE TABLE [dbo].[refRotationalRules](
	[NSN] [char](13) NOT NULL,
	[Rotate] [bit] NOT NULL
)

CREATE TABLE [dbo].[refRejectedRules](
	[GUID] [uniqueidentifier] NOT NULL,
	[NSN] [char](13) NOT NULL,
	[QTY] [int] NOT NULL
)

CREATE TABLE [dbo].[PersonDimension](
	[Person_ID] [varchar](30) NOT NULL,
	[First_Name] [varchar](30) NOT NULL,
	[Last_Name] [varchar](30) NOT NULL,
	[Middle_Initial] [char](1) NULL,
	[Email_Address] [varchar](30) NULL,
	[IsAdmin] [bit] NULL,
 CONSTRAINT [PK_PersonDimension] PRIMARY KEY CLUSTERED
(
	[Person_ID] ASC
)WITH (PAD_INDEX  = OFF, STATISTICS_NORECOMPUTE  = OFF, IGNORE_DUP_KEY = OFF,
ALLOW_ROW_LOCKS  = ON, ALLOW_PAGE_LOCKS  = ON) ON [PRIMARY]
)

CREATE TABLE [dbo].[ItemDimension](
	[NSN] [char](13) NOT NULL,
	[Length] [int] NULL,
```

```
	[Width] [int] NULL,
	[Height] [int] NULL,
	[Weight] [int] NULL,
	[Description] [varchar](500) NULL,
	[CanRotate] [bit] NULL,
	[CanStack] [bit] NULL,
 CONSTRAINT [PK_refDimensionalData] PRIMARY KEY CLUSTERED
(
	[NSN] ASC
)WITH (PAD_INDEX  = OFF, STATISTICS_NORECOMPUTE  = OFF, IGNORE_DUP_KEY = OFF,
ALLOW_ROW_LOCKS  = ON, ALLOW_PAGE_LOCKS  = ON) ON [PRIMARY]
)

CREATE TABLE [dbo].[TimeDimension](
	[Time_ID] [datetime] NOT NULL,
	[Minute] [int] NOT NULL,
	[Hour] [int] NOT NULL,
	[Day] [int] NOT NULL,
	[Month] [int] NOT NULL,
	[Year] [int] NOT NULL,
 CONSTRAINT [PK_TimeDimension] PRIMARY KEY CLUSTERED
(
	[Time_ID] ASC
)WITH (PAD_INDEX  = OFF, STATISTICS_NORECOMPUTE  = OFF, IGNORE_DUP_KEY = OFF,
ALLOW_ROW_LOCKS  = ON, ALLOW_PAGE_LOCKS  = ON) ON [PRIMARY]
)

CREATE TABLE [dbo].[RuleFactTable](
	[GUID] [uniqueidentifier] NOT NULL,
	[NSN] [char](13) NOT NULL,
	[Time_ID] [datetime] NOT NULL,
	[Person_ID] [varchar](30) NOT NULL,
	[Rule_ID] [int] NOT NULL,
	[QTY] [int] NOT NULL,
 CONSTRAINT [PK_RuleFactTable] PRIMARY KEY CLUSTERED
(
	[GUID] ASC,
	[NSN] ASC,
	[Time_ID] ASC,
	[Person_ID] ASC
)WITH (PAD_INDEX  = OFF, STATISTICS_NORECOMPUTE  = OFF, IGNORE_DUP_KEY = OFF,
ALLOW_ROW_LOCKS  = ON, ALLOW_PAGE_LOCKS  = ON) ON [PRIMARY]
)

ALTER TABLE [dbo].[RuleFactTable]  WITH CHECK ADD  CONSTRAINT
[FK_RuleFactTable_ItemDimension] FOREIGN KEY([NSN])
REFERENCES [dbo].[ItemDimension] ([NSN])
ON UPDATE CASCADE

ALTER TABLE [dbo].[RuleFactTable] CHECK CONSTRAINT [FK_RuleFactTable_ItemDimension]

ALTER TABLE [dbo].[RuleFactTable]  WITH CHECK ADD  CONSTRAINT
[FK_RuleFactTable_PersonDimension] FOREIGN KEY([Person_ID])
REFERENCES [dbo].[PersonDimension] ([Person_ID])
ON UPDATE CASCADE
```

```
ALTER TABLE [dbo].[RuleFactTable] CHECK CONSTRAINT [FK_RuleFactTable_PersonDimension]

ALTER TABLE [dbo].[RuleFactTable]  WITH CHECK ADD  CONSTRAINT
[FK_RuleFactTable_RuleDimension] FOREIGN KEY([GUID])
REFERENCES [dbo].[RuleDimension] ([Rule_ID])
ON UPDATE CASCADE
ON DELETE CASCADE

ALTER TABLE [dbo].[RuleFactTable] CHECK CONSTRAINT [FK_RuleFactTable_RuleDimension]

ALTER TABLE [dbo].[RuleFactTable]  WITH CHECK ADD  CONSTRAINT
[FK_RuleFactTable_TimeDimension] FOREIGN KEY([Time_ID])
REFERENCES [dbo].[TimeDimension] ([Time_ID])

ALTER TABLE [dbo].[RuleFactTable] CHECK CONSTRAINT [FK_RuleFactTable_TimeDimension]



/******  Database SQL ******/

CREATE TABLE [dbo].[ProblemInfo](
        [GUID] [uniqueidentifier] NOT NULL,
        [Name] [varchar](50) NOT NULL,
        [CreatedOn] [date] NOT NULL,
        [ModifiedOn] [date] NULL,
        [UseHistoricalData] [bit] NULL,
        [MinimumPercentage] [int] NULL,
 CONSTRAINT [PK_ProblemInfo] PRIMARY KEY CLUSTERED
(
        [GUID] ASC
)WITH (PAD_INDEX  = OFF, STATISTICS_NORECOMPUTE  = OFF, IGNORE_DUP_KEY = OFF,
ALLOW_ROW_LOCKS  = ON, ALLOW_PAGE_LOCKS  = ON) ON [PRIMARY]
)

CREATE TABLE [dbo].[ProblemDescription](
        [GUID] [uniqueidentifier] NOT NULL,
        [NSN] [char](13) NOT NULL,
        [QTY] [int] NOT NULL,
 CONSTRAINT [PK_ProblemDescription] PRIMARY KEY CLUSTERED
(
        [GUID] ASC,
        [NSN] ASC
)WITH (PAD_INDEX  = OFF, STATISTICS_NORECOMPUTE  = OFF, IGNORE_DUP_KEY = OFF,
ALLOW_ROW_LOCKS  = ON, ALLOW_PAGE_LOCKS  = ON) ON [PRIMARY]
)

CREATE TABLE [dbo].[SolutionInfo](
        [ProblemId] [uniqueidentifier] NOT NULL,
        [SolutionId] [uniqueidentifier] ROWGUIDCOL  NOT NULL,
        [CreatedOn] [date] NOT NULL,
        [CreatedDate] [datetime] NULL,
 CONSTRAINT [PK_SolutionInfo] PRIMARY KEY CLUSTERED
(
        [ProblemId] ASC,
        [SolutionId] ASC
```

```
)WITH (PAD_INDEX  = OFF, STATISTICS_NORECOMPUTE  = OFF, IGNORE_DUP_KEY = OFF,
ALLOW_ROW_LOCKS  = ON, ALLOW_PAGE_LOCKS  = ON) ON [PRIMARY]
)

CREATE TABLE [dbo].[ShipComparison](
        [ShipName] [varchar](200) NOT NULL,
        [HistoricalDataKey] [varchar](50) NOT NULL,
        [ProblemId] [uniqueidentifier] NOT NULL,
        [MappingId] [int] IDENTITY(1,1) NOT NULL
)

CREATE TABLE [dbo].[MinValueComparison](
        [Id] [int] IDENTITY(1,1) NOT NULL,
        [ShipName] [varchar](200) NOT NULL,
        [NoMinId] [uniqueidentifier] NOT NULL,
        [Minof10Id] [uniqueidentifier] NOT NULL,
        [Minof20Id] [uniqueidentifier] NOT NULL,
        [Minof30Id] [uniqueidentifier] NOT NULL,
        [Minof40Id] [uniqueidentifier] NOT NULL,
        [Minof50Id] [uniqueidentifier] NOT NULL,
        [Minof60Id] [uniqueidentifier] NOT NULL,
        [Minof70Id] [uniqueidentifier] NOT NULL,
        [Minof80Id] [uniqueidentifier] NOT NULL,
        [Minof90Id] [uniqueidentifier] NOT NULL,
 CONSTRAINT [PK_MinValueComparison] PRIMARY KEY CLUSTERED
(
        [Id] ASC
)WITH (PAD_INDEX  = OFF, STATISTICS_NORECOMPUTE  = OFF, IGNORE_DUP_KEY = OFF,
ALLOW_ROW_LOCKS  = ON, ALLOW_PAGE_LOCKS  = ON) ON [PRIMARY]
)

CREATE TABLE [dbo].[SolutionDescription](
        [SolutionId] [uniqueidentifier] NOT NULL,
        [ContainerNumber] [int] NOT NULL,
        [NSN] [char](13) NOT NULL,
        [QTY] [int] NOT NULL,
        [RuleId] [uniqueidentifier] NOT NULL,
 CONSTRAINT [PK_SolutionDescription] PRIMARY KEY CLUSTERED
(
        [SolutionId] ASC,
        [ContainerNumber] ASC,
        [NSN] ASC
)WITH (PAD_INDEX  = OFF, STATISTICS_NORECOMPUTE  = OFF, IGNORE_DUP_KEY = OFF,
ALLOW_ROW_LOCKS  = ON, ALLOW_PAGE_LOCKS  = ON) ON [PRIMARY]
)


ALTER TABLE [dbo].[SolutionInfo]  WITH CHECK ADD  CONSTRAINT
[FK_SolutionInfo_ProblemInfo] FOREIGN KEY([ProblemId])
REFERENCES [dbo].[ProblemInfo] ([GUID])

ALTER TABLE [dbo].[SolutionInfo] CHECK CONSTRAINT [FK_SolutionInfo_ProblemInfo]

ALTER TABLE [dbo].[SolutionInfo] ADD  CONSTRAINT [DF_SolutionInfo_SolutionId]  DEFAULT
(newid()) FOR [SolutionId]
```

```
ALTER TABLE [dbo].[ProblemDescription]  WITH CHECK ADD  CONSTRAINT
[FK_ProblemDescription_ProblemInfo] FOREIGN KEY([GUID])
REFERENCES [dbo].[ProblemInfo] ([GUID])
ON DELETE CASCADE

ALTER TABLE [dbo].[ProblemDescription] CHECK CONSTRAINT
[FK_ProblemDescription_ProblemInfo]
```

VITA

Lucien Millette has a Bachelor of Arts degree with majors in both Mathematics and Computer Science from the College of the Holy Cross, 2006, and expects to graduate from the University of North Florida with a Master of Science in Computer and Information Sciences in April of 2012. Dr. Behrooz Seyed-Abbassi is serving as Mr. Millette's thesis advisor.

Mr. Millette has worked for CGI Federal for the past six years. His current position is as the Project Manager for software development on the Prepositioning Plans and Data Support Contract assisting the United States Marine Corps.