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by

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ABSTRACT

The objective of this project was to develop an automated method of finding a near optimal set of assignments of trucks and shipments for a regional carrier. An existing computer system was enhanced to give the regional carrier a quick initial solution based on quantitative and qualitative criteria. The Hungarian method was selected for initial minimization of assignments because of its minimal computer processing time. In addition, a heuristic was developed to rerun the model based on qualitative issues. The combination of quantitative and qualitative analysis provides the regional carrier with an effective decision-making tool.

ACKNOWLEDGEMENT

This project was supported in part by the management information consulting division of Arthur Andersen & Co. in Dallas, Texas. In particular, I would like to thank Dallas consulting partner Mike Gelhausen and consultants Tim Albright and Lisa Leonard for their cooperation, time, and input. In addition, I would like to thank two operations research professors at Southern Methodist University, Drs. Jose Dula and Richard S. Barr, for their time and input.

BACKGROUND

Regional trucking companies have a dynamically changing environment. Many variables which affect management decisions on assignments of trucks and shipments continuously change. Management must record the changes promptly and correctly in order to make effective decisions.

Burlington Northern Motor Carriers, Inc. approached Arthur Andersen & Co. in March 1987 about the development of a system that would quickly record decision-making values. Burlington Northern Motor Carriers transport goods throughout the United States. Five regions handle all of BNMC's business. Each region services its local shipments, but each region may ship to another region. When trucks and trailers arrive in a region, it is the responsibility of the carrier in the arrival region to reschedule the trucks and trailers for the next haul.

The rescheduling function is a manual process involving written reports and telephone calls from truckers' district managers to load dispatchers, who assign trucks and shipments in each region. BNMC's objective is to keep the trucks moving. Time pressures force load dispatchers to make assignments in a very short time frame. Thus, it is often uneconomical (or too complex) for the load dispatcher to consider every available or inbound truck for comparison.

Arthur Andersen & Co. developed an artificial intelligence system called Micro Dispatch. Micro Dispatch makes better use of the load dispatcher's time by allowing the load dispatcher quick access to information about truck/shipment matches.

The technical environment of Micro Dispatch is an artificial intelligence workstation (TI Explorer). The program was written in LISP with an articial intelligence programming tool called KEE, which was developed by Intellicorp.

The Micro Dispatch program is responsible for the region which contains Dallas/Fort Worth. The knowledge base contains information on shipments, trucks, drivers, and trailers. All pertinent information to the decision-making process of assignments is stored in the knowledge base. A list of the most critical decision-making elements in the knowledge base are as follows:

-- Delivery/pickup time windows: The system calculates the distance from the truck to the shipment, estimates the time to travel that distance, and checks to see if the resultant time is within the pickup time. The same procedure determines if delivery windows are obtainable.

-- Type of trailer: Six kinds of trailers exist - 43R, 48R, 53R, 43D, 48D, 53D. The first two numbers denote length of trailer; the letter denotes whether or not the trailer is refridgerated (R=refridgerated, D=dry van).

-- Total mileage: Minimize number of deadhead miles (miles without a load) and load miles (miles with a shipment).

-- Domocile contracts: BNMC hires independent truckers. When a trucker is hired, he has a domocile contract, which is a verbal commitment from BNMC that thr driver will receive a few days of rest after a specified number of working days. Dispatchers try to schedule shipments near the driver's home towards the end of a domocile contract to keep the driver happy. The dispatcher does not have to adhere to the domocile contract because it is only a verbal agreement. However, the dispatcher runs the risk of losing a driver if the driver works too many days past his domocile contract.

-- Driver type: Two types of drivers exist. Single drivers must rest according to Department of Transportation regulations if the shipment is a long haul. Team drivers can alternate resting periods, keep the truck moving, and meet deadlines within DOT regulations for shipments with long hauls.

-- DOT regulations: A driver can only drive for eight consecutive hours. Between eight hour driving periods, the driver must rest at least ten hours.

-- Maintenance: Trucks have routine maintenance at 5000 mile intervals.

-- Unloading: Some pickups and deliveries require that the driver help load/unload the shipment. Also, some drivers cannot or will not load/ unload shipments.

The load dispatcher can access any of the information in the knowledge base. Trucks and shipments are graphed against a backgound map (see Figure 1 on next page). The map is a "mouse sensitive" picture. A "mouse sensitive" picture allows the load dispatcher to quickly access specialized menus of functions about all trucks/shipments or specific trucks/shipments, depending on how the load dispatcher uses the "mouse" on the map.

Micro Dispatch features several functions. The load dispatcher can assign or unassign trucks and shipments. The load dispatcher can generate a list of match-ups of trucks and shipments that meet pickup/delivery windows and trailer

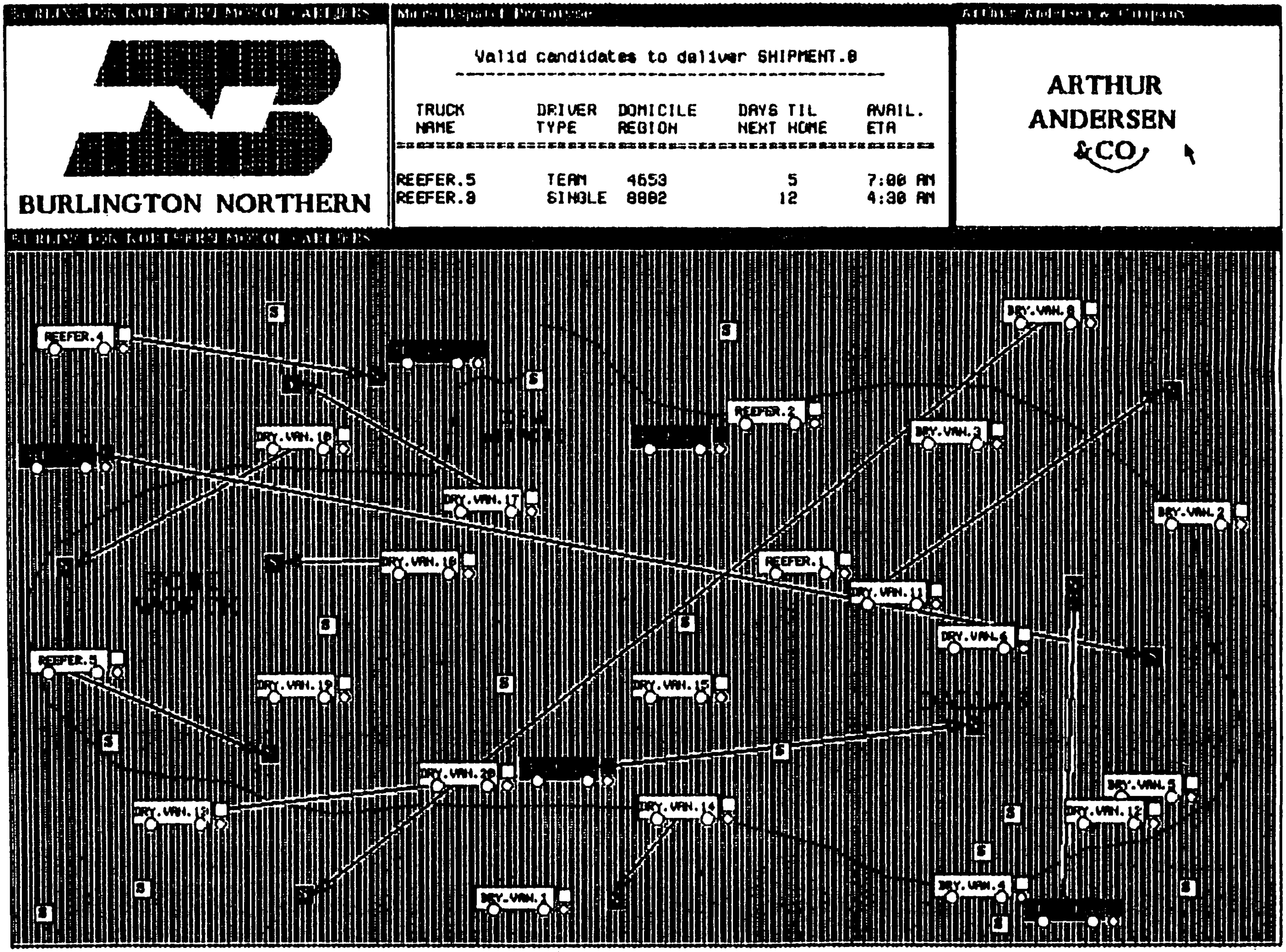

BURLINGTON NORTHERN
Valid candidates to deliver SHIPMENT.8
TRUCK NAME
DRIVER TYPE
DOMICILE REGION
DAYS TIL NEXT HOME
AVAIL. ETA
REEFER.5 TEAM 4653 5 7:00 AM
REEFER.9 SINGLE 8882 12 4:30 AM
ARTHUR ANDERSEN &CO
REEFER.4
DRY.VAN.8
REEFER.2
DRY.VAN.10
DRY.VAN.3
DRY.VAN.17
DRY.VAN.2
DRY.VAN.16
REEFER.1
DRY.VAN.11
DRY.VAN.6
REEFER.5
DRY.VAN.19
DRY.VAN.15
DRY.VAN.20
DRY.VAN.13
DRY.VAN.14
DRY.VAN.5
DRY.VAN.12
DRY.VAN.4
DRY.VAN.1

Figure 1

type for a selected truck or shipment. The system can also show reasoning for invalid match-ups. In addition, the system has an ability to give information about any truck or shipment.

DEFINITION OF PROJECT

Micro Dispatch was developed in approximately two weeks, and it is somewhat limited in scope. Several additions to reasoning power of the system are possible. The most significant of these additions is the ability to optimize assignments of all unassigned trucks and shipments.

The optimization of assignments should include reasoning about driver domocile contracts, truck preventative maintenance, hot shipments (priority shipments called to the load dispatcher's attention at the last minute), and preferred driver/shipment assignments.

The optimization needs to be a near optimal solution in a minimal amount of time. BNMC wants a quick, near optimal solution because the ever-changing environment requires quick decisions. The optimization program will produce a list of suggested assignments of trucks and shipments based on information in the current, updated knowledge base.

The model must assign an average of fifteen trucks to fifteen shipments. In addition, the model does not have to schedule future assignments. BNMC does not want to schedule future pickups and deliveries because of problems in the coordination of the five regions and the inevitable dynamic changes which dramatically affect delivery times.

In addition, the model must be coded in LISP, because the TI Explorer which contains the knowledge base, is a specially configured computer for LISP.

OVERVIEW OF APPROACH

A distinct advantage of the LISP machine and knowledge base is the ability to perform qualitative analysis based on the output of numeric models. The system can perfrom sensitivity analysis on the output, similar to how a human functions. This advantage is important because of the BNMC decision-making environment.

The disadvantage of the BNMC decison-making environment is the inability to assign numeric values to goals of the company. For example, it is difficult to assign a numeric value to the goal of meeting a domocile contract, preventative maintenance, hot shipments, or preferred driver assignments. These goals are good, but only if the company does not sacrifice too many deadhead mileage to attain them.

Although strict values cannot be obtained, several guidelines can be assumed. Assignment changes because of domicile contracts are valid if the driver is less than two days from his rest period and the alternate trip costs the company only half as many miles as the number of miles that he gets closer to home.

Preventative maintenance should be considered only if the new trip exceeds approximately 1000 miles or the new assignment results in fewer than 1000 cumulative miles on other trucks.

Hot shipments and preferred driver assignments should be considered if the number of extra miles is less than double of the miles for the alternate shipment.

Although numeric guidelines exist, they are relative to the initial optimal numeric solution. The values are known only after an initial solution based solely on mileage and time windows.

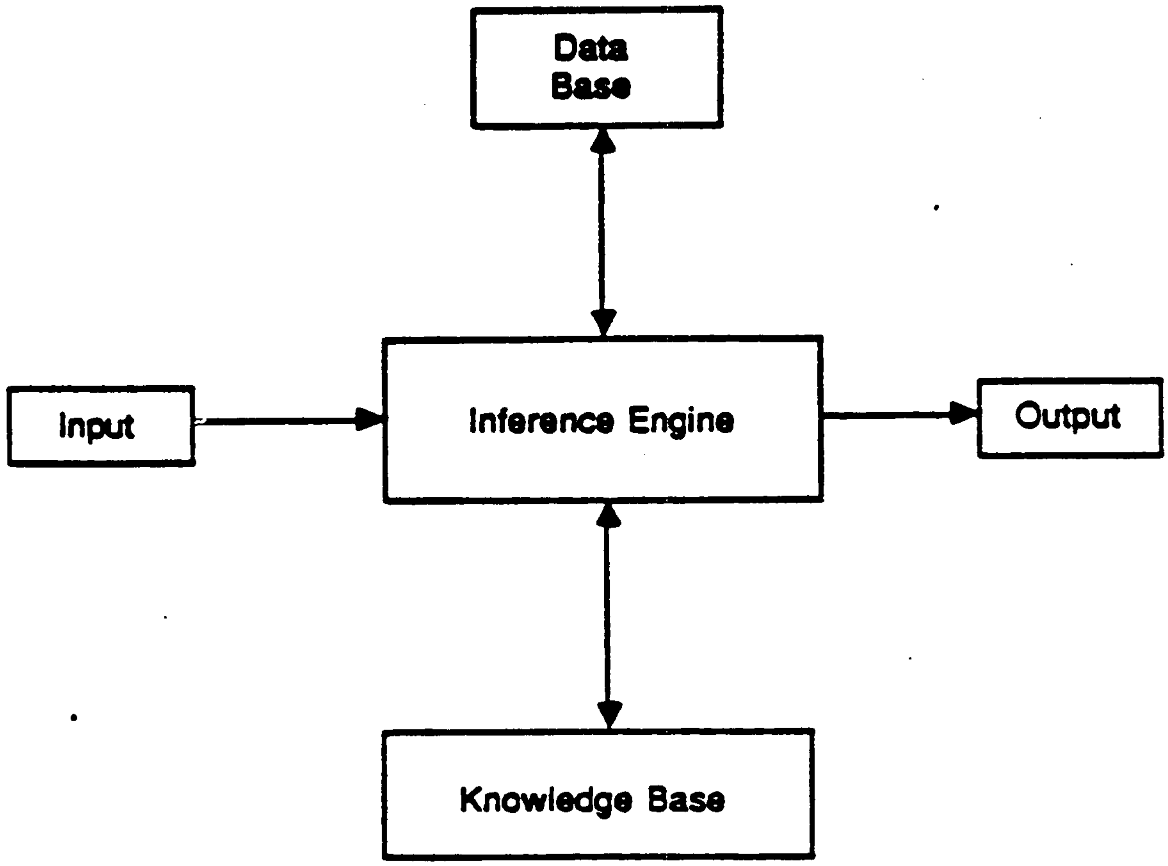
BNMC does not have a strict numeric value for each decision because the issues are qualitative, not quantitative. They expressly told Arthur Andersen & Co that they do not see linear programming as a viable alternative because the numbers for these goals are not concrete. The values are always relative to other assignments.

In addition to the disadvantage of lack of numeric values, BNMC's dynamically changing environment renders models useless after a change in the environment. For example, if a load dispatcher had assigned an inbound truck to a shipment and the inbound truck had a flat tire, the model would have to be updated and rerun to find an alternative assignment for the previously assigned shipment.

Artificial intelligence is a powerful tool because of the independence of data (knowledge base) and the program (inference engine). As seen in Figure 2 (see next page), the inference engine reads the knowledge base and derives at decisons based on the data. Artificial intelligence can create the model for each new knowledge base. For the previous example, the load dispatcher updates the knowledge

Figure 2

EXPERT SYSTEMS ARCHITECTURE



NOTES:

- Expert systems replace the procedural program with an inference engine and knowledge base.
- The knowledge base has declarations of knowledge specific to the application, such as rules and facts.
- The inference engine has pre-defined algorithms that control data input, output, and processing.

base to delay the truck for the length of a tire change, and he reruns the model. The inference engine models according to the new data in the knowledge base.

The solution to the problem will be two fold. First, a minimization model will find an initial assignment of trucks to shipments based on mileage and time windows. The second part of the model will analyze alternate selections and the impact on the initial assignments.

PART ONE: TWO ALTERNATIVES FOR MINIMIZING MILEAGE

Two alternative model techniques were considered for minimizing total mileage and time windows -- the simplex method and the Hungarian method.

The Simplex method

When analyzing the decison-making environment of BNMC, it is important to remember the objective of the optimization model. The objective of the model is the creation of a quick list of suggested assignments. Time is the main disadvantage of the simplex method.

The simplex method would require approximately 225 variables (an average of fifteen trucks and fifteen shipments). Some of those variables could be eliminated because of failure for trucks to meet time windows, but only some of those variables. Therefore, 225 variables is a reasonable assumption.

The objective of the model is as follows:

$$\min \sum_{j=1}^{m} \sum_{i=1}^{n} C_{ij} X_{ij}$$

where i = all unassigned shipments
= 1,2,...,n
j = all available and inbound trucks
= 1,2,...,m

The contraints can be outlined as follows:

$$\sum_{i=1}^{n} X_{ij} = 1$$ only one shipment can be assigned to one truck; for j = 1,...,m

$$\sum_{j=1}^{m} X_{ij} = 1$$ only one truck can be assigned to one shipment; for i = 1,...,n

The simplex method's time to find an initial solution depends on the number of variables[1]. Since the average number of variables in the model is 225, the number of iterations could be lengthy.

In addition, the simplex method may find an infeasible solution. If a shipment does not have any trucks which meet the time windows, trailer type, maintenance, or unloading requirements, the model would not assign any trucks to the shipment. Additional constraints would be difficult to create because assignment problems modelled by the simplex method require constraints with the right-hand side values equal to one[2]. Therefore, the model would have to leave the shipment out of the model, which is a misrepresentation of the real world.

The Hungarian Method

The Hungarian method is the best known technique for solving the assignment problem[3]. The model consists of the following:

$$\min \sum_i u_i + \sum_j v_j$$

subject to $u_i + v_j <= c_{ij}$ for all i,j

Each u(i) is associated with a truck constraint and each v(j) with a shipment constraint. If each element c(ij) is reduced by u(i) and v(j) on a given cost matrix, the net effect on the matrix is nothing. The relative costs remain unchanged.

The Hungarian method uses the reduction property to reduce the original cost matrix of trucks and shipments until the elements associated with the optimal solution are all zero.

The Hungarian method relies on Konig's theorem to test whether or not an optimal solution exists:

> If the elements of a matrix are divided into two classes by property R, then the minimum number of lines drawn through rows or columns needed to cover all elements with property R is equal to the maximum number of elements with the property R where no two such elements appear in the same row or column[4].

At each iteration the Hungarian method reduces the matrix so that at least one zero (property R) exists in every column and row. Konig's theorem tells the system if an optimal solution exists. If the minimum number of lines using the theorem equals the maximum number of rows assigned to columns of zero elements (hence, trucks assigned to shipments), the optimal assignment exists.

Times taken for iterations on the Hungarian method as programmed in the TI Explorer in LISP for this model are less than a second for an average sized matrix of 15 X 15 elements. Therefore, this method meets the BNMC requirement of speed.

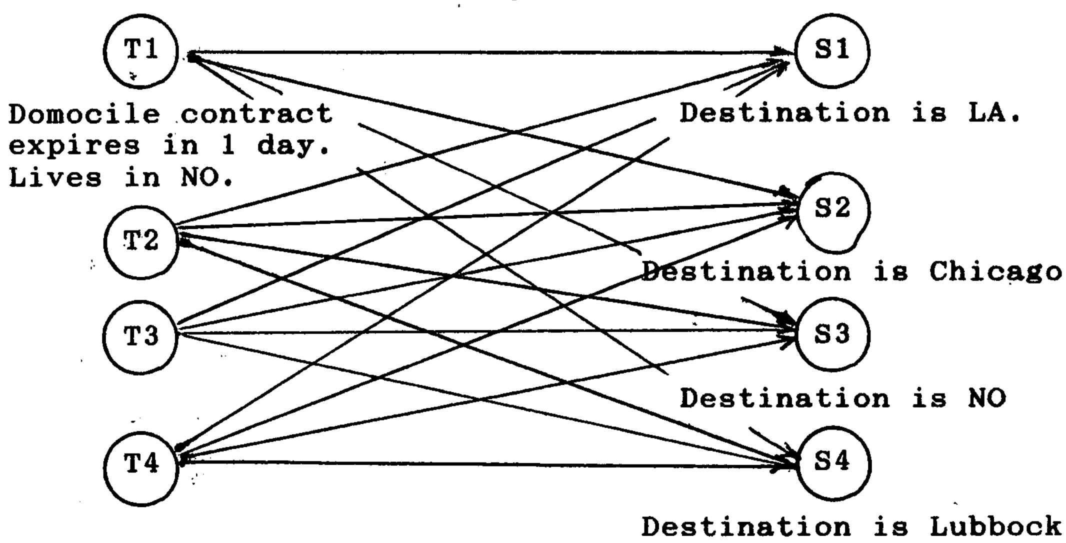
PART TWO: ALTERNATE SELECTIONS

The advantage of artificial intelligence is the ability to analyze solutions similar to a human. In the BNMC environment, the next logical step after obtaining an intial solution is the detection of alternate selections which meet general, subjective, and qualitative criteria.

An alternate selection will be made if one of the general guidelines discussed in the overview of approach appears in the matrix. For example, look at the following matrix:

6	4	1	5
10	6	3	8
7	6	4	5
9	10	3	8

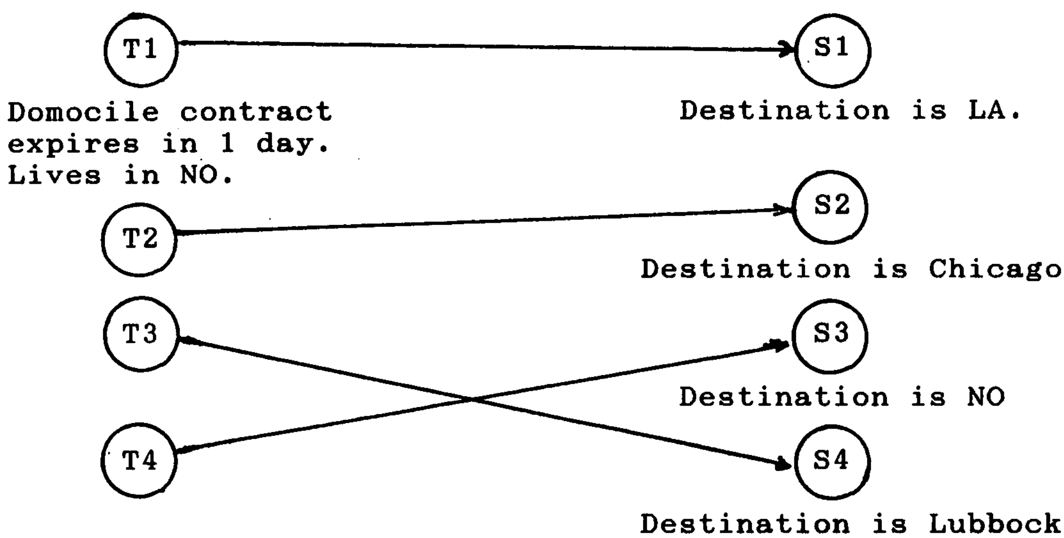
This matrix is the mileage matrix of the following network of available trucks and shipments:



The optimal solution of the reduced mileage matrix is the following:

0	0	0	1
2	0	0	2
0	1	2	0
1	4	0	2

Pictorially, the optimal solution is as follows:



Although the optimal solution assigns truck one to deliver shipment one to LA, the domocile contract would obviously be violated because the trip from Dallas to LA would take more than one day, and the driver would be over 2000 miles from home.

By looking at the original matrix, the obvious solution is the assignment of truck one to shipment three because the shipment is due in the driver's domocile city. When the Hungarian method reruns for the alternate assignment in this example, the incurred extra mileage meets the guideline for alternate assignments of domocile contract. Therefore, the alternate selection is made.

The artificial intelligence model makes inferences based on the original and reduced matrices. If an alternate selection appears to cost less than the guidelines, the original matrix is rerun without the alternate assignment. If the costs of an new assignments created by the alternate assignment are within general guidelines, the alternate selection is made.

Decisions of alternate selection are based on the initial matrix optimization. The original matrix gives the values for which alternate selection criteria is based. Decisions are made based on the relative change in the solution.

In addition to the alternate selections based on domocile contracts, alternate selections can be made based on preventative maintenance, hot shipments, and preferred carriers in the same general approach. The alternate selection is made, the model rerun, and the results are compared to the guidelines. If the alternate selection meets the general guidelines, the alternate selection is made.

CONCLUSION

An artificial intelligence program in this particular environment is advantageous. The artificial intelligence allows the data in the knowledge base at an instantaneous place in time to drive a quick and optimal solution.

Values of goals are often hard to make absolute. For example, the value of meeting a domocile contract is dependent on the effect to the other assignments. A domocile contract value of 1000, 1250, or 1998 is impossible to derive before the load dispatcher runs the model. The value is only known after the initial solution based on total mileage.

The Micro Dispatcher optimization program enhances the load dispatcher's decision-making process with the addition of a tool that optimizes assignments based on his criteria. Values for qualitative issues are relative and not forced on the model.

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