A Study on the Solution Approach for Dynamic Vehicle Routing Problems under Real-time Information

Ta-Yin Hu
Department of Traffic and Transportation Engineering and Management
Feng Chia University, Taichung, Taiwan
TEL: 886-4-24517250 - 4650
FAX: 886-4-24511173
EMAIL: tyhu@fcu.edu.tw

Tsai-Yun Liao
Department of Information Management
Chao Yang University of Technology, Taichung, Taiwan, R.O.C.

Ying-Chih Lu
Department of Traffic and Transportation Engineering and Management
Feng Chia University, Taichung, Taiwan, R.O.C.

July 31 2002
Revised, Nov. 15, 2002

Number of words: approximately 5,900 words.

Submitted for presentation at the Annual Meeting of the Transportation Research Board,
A Study on the Solution Approach for Dynamic Vehicle Routing Problems under Real-time Information

Ta-Yin Hu
Department of Traffic and Transportation Engineering and Management
Feng Chia University, Taichung, Taiwan

Tsai-Yun Liao
Department of Information Management
Chao Yang University of Technology, Taichung, Taiwan, R.O.C.

Ying-Chih Lu
Department of Traffic and Transportation Engineering and Management
Feng Chia University, Taichung, Taiwan, R.O.C.

ABSTRACT

Recent advances in Commercial Vehicle Operations (CVO), especially in communication and information technologies, allow the study of dynamic vehicle routing problems under new and updated information, such as traffic conditions and new customers. Two major operational benefits of CVO include: (1) dynamically assign vehicles to time-sensitive demands, and (2) efficiently reroute vehicle according to current traffic conditions.

In this research, stochastic vehicle routing problems (SVRP) are considered and extended to incorporate real-time information for dynamic vehicle routing problems (DVRP). The SVRP model is formulated by a chance-constrained model, and is solved by CPLEX with branch-and-bound techniques.

Numerical experiments are conducted in a Taichung City Network to investigate dynamic vehicle routing strategies under real-time information supply strategies, and to assess the effectiveness of such strategies in a dynamic perspective.

Keywords: dynamic vehicle routing problem, stochastic vehicle routing problems,
simulation-assignment, real-time information

INTRODUCTION

Recent advances in Commercial Vehicle Operations (CVO), especially in communication and information technologies, allow the study of dynamic vehicle routing problems under new and updated information, such as real-time traffic conditions, vehicle status, and new coming demands (1). Dynamic vehicle dispatching and routing strategies are important aspects of Commercial Vehicle Operations (CVO) applications of ITS. Two major operational benefits of CVO include: (1) dynamically assign vehicles to time-sensitive demands, and (2) efficiently reroute vehicle according to current traffic conditions. One critical problem in vehicle dispatching is vehicle routing problem (VRP) in real time.

VRP and its variants have been studied for several decades. Although most real-world vehicle routing problems are dynamic, and the traditional methodologies for this class of problems has been based on adaptations of static algorithms. These routing strategies are developed under static travel time, but they do not consider real-time traffic flow conditions. Dynamic vehicle routing problems need to consider real-time information as well as demands, and thus information attributes are important to the DVRP (2).

Stochastic Vehicle Routing Problems (SVRP) arise whenever some elements of the problems are random, such as random quantities at the various customers, stochastic demands and stochastic travel time. In the VRP with Stochastic Travel Times (VRPST), the travel times on links are assumed to be random variables due to traffic conditions. All authors who have treated this problem attempt to determine a priori solution such that the probability of completing the tour within a given deadline is maximized. SVRPs are often regarded, as computationally intractable and good heuristics are hard to design and assess (3,4).

The research is based on the framework proposed by Hu (5), and a SVRP formulation (4) is adopted and solved to model dynamic vehicle routing problems. The proposed framework incorporates traffic simulation, vehicle route updating, and real-time information in an integrated system. The traffic simulation and vehicle route assignment are accomplished through the simulation-assignment model, DYNASMART. The stochastic vehicle routing problem (SVRP) approach is adopted and modified to
incorporate real-time information.

This paper is organized as follows: the next section briefly describes some related research. The evaluation framework and SVRP formulation are discussed in the third section, followed by numerical experiments and analysis. Concluding comments are given in the last section.

LITERATURE REVIEW

The fleet management problem includes two types of subproblems: fleet assignment problem and routing problem (6). Assume a dispatcher uses a fleet of vehicles of limited capacity to serve a set of demands. First, the dispatcher must decide how to partition the demands into groups that can be served by a vehicle. Second, the dispatcher must decide what sequence to use so as to minimize cost.

The Vehicle Routing Problem (VRP) is the problem of constructing vehicles routes of minimum total cost starting and ending at a depot, such that each node is visited by one vehicle, and satisfying some constraints, such as capacity, duration, and time windows. Since the VRP problem is NP-Hard, different solution techniques, including heuristics, mathematical programming based heuristics, meta-heuristics, and polyhedral combinatorics based optimization algorithms, are applied to obtain acceptable solutions within a reasonable time frame.

Stochastic Vehicle Routing Problems (SVRP) arise whenever some elements of the problems are random, such as random quantities at the various customers, stochastic demands and stochastic travel time. In the VRP with Stochastic Travel Times (VRPST), the travel times on links are assumed to be random variables due to traffic conditions. All authors who have treated this problem attempt to determine a priori solution such that the probability of completing the tour within a given deadline is maximized. A limited literature has evolved around stochastic formulations for a stochastic version of the classical vehicle routing problem (3,4). However, all of these papers focus primarily in a two-stage formulation where vehicle routes are designed prior to knowing customer demands; however, traffic characteristics, such as variations of flow and types of intersection control, are still not considered.

With the advancement of communication and information technologies, real-time traffic conditions as well as dynamic demands are possible to obtain during the vehicle’s
journey, thus a realistic vehicle routing problem is defined as dynamic vehicle routing problems (DVRPs). Psaraftis (6) has addressed some basic characteristics of dynamic vehicle routing problem, and pointed out that computer and communication technologies, such as electronic data interchange (EDI), geographic information systems (GIS), global positioning systems (GPS), and Intelligent Transportation Systems (ITS), have significantly enhanced the possibilities for efficient dynamic routing. Possible information attributes might include evolution of information (static/dynamic), quality of information (known-deterministic /forecast /probabilistic /unknown), availability of information (local/global), and processing of information (centralized/decentralized)(6). These information attributes might have great impact on how to develop and design an efficient and good dynamic vehicle routing algorithms.

Gendreau et al. (1) propose a tabu search heuristic approach to the dynamic VRP and implemented on a parallel computer platform to increase the computational effort. Due to the difficulties of capturing the variation of travel time in a traffic network, simulation models have been used to generate realistic travel time and applied in different routing strategies. Taniguchi et al. (7) develop a probabilistic vehicle routing and scheduling model incorporates the variation of travel times though a dynamic traffic simulation model. Hu (5) provides an evaluation framework under the consideration of real-time information, and the vehicle routing strategies are solved through a heuristic approach.

FRAMEWORK AND SOLUTION APPROACH

The research aims at developing a solution approach based on SVRP for the dynamic VRP, and the solution strategy is then evaluated in a realistic traffic simulation framework. The overall research structure is depicted in Figure 1 (5). Three basic components are in this framework, namely, simulation-assignment model, vehicle routing process, and advanced traffic information system. Thus, dispatching and routing operations could take full advantage of real-time information on vehicle locations and demands as well as current traffic conditions.

The proposed evaluation framework is used to study the effectiveness of real-time routing strategies. Basic inputs of the framework include vehicles with associated attributes, traffic network descriptions, and other data, such as traffic control. Within
this framework, vehicles, including commercial or other special vehicles, could be sent out by dispatchers to handle specific demands. The simulation-assignment model - DYNASMART is used to simulate time-dependent flow patterns, and real-time information is processed to design dynamic dispatching strategies, and the results are assigned back to commercial vehicles.

The solution approaches for the dynamic VRP are implemented in two phases: route generation and route improvement. The original route is generated according to travel time under free flow conditions through a mathematical formulation. Since the travel time is affected by current traffic condition, a chance-constrained model (4), which considers travel time uncertainty in terms of mean and variance, is developed and solved. The chance-constrained mathematical model is implemented according to dynamic travel time information and associated variances. Then, the dynamic route information is provided to commercial vehicles to achieve real-time route improvement. Due to the complexity of the model, the chance-constrained model is solved by CPLEX, a mathematical programming software.
The following SVRP formulation proposed by Laporte et al. (4) is implemented in this research with considerations of traffic conditions and travel time specifications. The chance-constrained model primarily solves a stochastic problem by an additional constraint, in which the probability of travel time greater than B must less than a threshold $\alpha$. The formulation is illustrated as follows:

$$\text{Minimize } \sum_{x,m} c_{ij} x_{ij}$$

Subject to
\begin{align*}
\sum_{i=1}^{n} x_{0j} &= 2m \quad (2) \\
\sum_{i=1}^{n} x_{ij} &= 1 \quad (3) \\
\sum_{j=1}^{n} x_{ij} &= 1 \quad (4)
\end{align*}

Illegal route elimination constraints

\[ x_{ij} \in \{0; 1\} \quad (6) \]

\[ X = (x_{ij}) \in S \quad (7) \]

\[ m \geq 1 \text{ and } m \text{ is integer} \quad (8) \]

\[ P\left(\sum_{k=0}^{n}[v_{i_k}+\tau_i]x_{ij} > B\right) < \alpha \quad (9) \]

\( x_{ij} \): decision variable for route sequence, such as \( x_{ij} = 1 \) means the route include the link \((i,j)\); \( 0 \) means that link \((i,j)\) is not included.

\( f \): fixed cost for \( m \) vehicles

\( m \): number of vehicles

The objective function represents the combination of vehicle travel cost and vehicle costs. All other constraints are self-explanatory. Illegal route elimination constraints could be formulated in different ways, and the one used is as follows:

\[ \sum_{i \in R} \sum_{j \in R} x_{ij} \leq |R| - 1 \quad R: \text{a subset of the node set}\{2, 3, \ldots n\} \quad (10) \]

Equation (9), the additional constraint, is discussed next. The chance-constrained model is attractive and relatively simple to solve. However, there are several parameters needs to be determined in advance. The concept of chance constrained programming approach is discussed next, followed by a discussion of implementation issue.

**Chance-Constrained Programming**

The stochastic programming approach requires that all the functional constraints must hold for all possible solutions, and the chance-constrained programming approach
requires only that each constraint must hold for most of these combinations. The formulation replaces the deterministic constraints

\[ \sum_{j=1}^{n} a_{ij}x_j \leq b_i \]  \hspace{1cm} (11)

By

\[ P \left\{ \sum_{j=1}^{n} a_{ij}x_j \leq b_i \right\} \geq \alpha_i \]  \hspace{1cm} (12)

where the \( \alpha \) are specified constants between zero and one (although they are normally chosen to be reasonably close to one). Therefore, a nonnegative solution is considered to be feasible if and only if

\[ P \left\{ \sum_{j=1}^{n} a_{ij}x_j \leq b_i \right\} \geq \alpha_i \]  \hspace{1cm} (13)

Each complementary probability, \( 1-\alpha \), represents the allowable risk that the random variables will take on such values that

\[ \sum_{j=1}^{n} a_{ij}x_j > b_i \]  \hspace{1cm} (14)

Thus, the objective is to select the “best” nonnegative solution that “probably” will turn out to satisfy each of the original constrained when the random variables take on their values. The equation could be presented as the following equation:

\[ P \left\{ \sum_{j=1}^{n} a_{ij}x_j \leq b_i \right\} = P \left\{ \frac{\sum_{j=1}^{n} a_{ij}x_j - E(b_i)}{\sigma_{b_i}} \leq \frac{b_i - E(b_i)}{\sigma_{b_i}} \right\} \]  \hspace{1cm} (15)

E (\( b_i \)) and \( \sigma_{b_i} \) represent expectation and standard deviation of \( b_i \).

The SVRP formulation is directly solved through CPLEX. CPLEX includes a callable C library that makes it easier to develop applications to optimize, to modify, and to interpret the results of mathematical programming problems whether linear, mixed integer, or convex quadratic ones. The CPLEX Mixed Integer optimizer, or MIPS optimizer, exploits a branch-and-bound algorithm.

As shown in Figure 2, vehicles are generated according to a time-dependent OD matrix and assigned to historical paths; however, commercial or other special vehicles
are assigned by dispatchers. All these vehicles are loaded into DYNASMART. Assume time-dependent flow distribution could be estimated according to surveillance and monitoring systems, such as detectors and/or vehicles equipped with GPS.

![Diagram of Dynamic Routing Strategies]

**FIGURE 2. Evaluation of Dynamic Routing Strategies**

Dynamic routing strategies then could be developed under two situations: single OD pair and multiple demands. In the first situation, a time-dependent shortest path is calculated according to the current flow distributions. For multiple demands, a sequence of demand nodes needs to be determined; therefore, a node-to-node travel time matrix is calculated according to all-pairs shortest path algorithms, such as the
Floyd-Warshall algorithm(9). The matrix is used by the SVRP solver to design the optimal sequence of demand nodes. These paths and/or routes are again assigned to commercial vehicles.

Algorithmic Procedures

The dynamic vehicle route updating procedure is summarized as follows:

Step 1. Initialization

Generate vehicles' attributes and historical paths. Obtain a set of paths from origin r to destination s for each discrete departure time interval j. Assign to each tripmaker i a set of static and run-time attributes, and a set of behavior attributes Bi.

Step 2. Network Loading

For each tripmaker i, assign a path \( k_i \) from r to s, \( k_i \in K_{r,s,j} \), and a loading location, i.e. generation link. \( K_{r,s,j} \) is the set of paths from r to s at time interval j.

Step 3. Traffic Simulation

Simulate time-dependent flow distribution by DYNASMART. Obtain traffic flow distribution condition, such as link travel time and node transfer time.

Step 4. Single-OD Real-Time Path generation

For a vehicle with in-vehicle information systems (or on-board unit), it will receives the best route under real-time information.

Step 5. Routing Strategies

Assumed a delivery/pickup truck has a list of visit demand nodes, and it is required to visit them at least once. In this procedure, a route will be generated according to a specified method.

Step 5a. Travel Time Matrix Generation

In order to design an efficient route, the travel time matrix in a traffic network is generated by Floyd-Warshall Algorithm.

Step 5b. Route Generation by SVRP

After solving the all pair shortest-path problem, travel time information is used to calculated mean travel time and associated standard deviation for each pair of demand nodes.

The SVRP formulation is solved by CPLEX on a PC, and the output is transferred back to DYNASMART. In order to update vehicle route as the
vehicle travels in the network, travel time cost and associated standard deviation are adjusted to include node-to-depot and current node to demand nodes.

**Step 6. Path, Route Strategies**

The generated path and route are assigned to different vehicles. The path and/or route for commercial vehicles could be updated according to predetermined steps in order to reflect the time-dependent nature of traffic flows.

From this evaluation framework, two major outputs can be obtained, namely overall system performance and individual vehicle statistics. Overall system performance describes basic travel statistics, such as average travel time (ATT), average stopped time (AST), and average travel distance (ATD). Individual vehicle statistics include vehicle trajectory, demand node sequence, and paths between each neighboring demand nodes.

![Diagram of information interchange between CPLEX and DYNASMART](image)

**FIGURE 3. Information Interchange Between CPLEX and DYNASMART**

In order to apply SVRP in an iterative scheme with changing demand nodes, several conversions are summarized as follows:
1. During the SVRP calculation, the number of demand nodes are reducing as the vehicle travels and finishes the service for demand nodes.
2. The depot is changing along the route, and the travel cost matrix is adjusted as well. The beginning node is set as the current network node, and the ending node is set as the original depot.

**NUMERICAL EXPERIMENTS AND RESULTS**

Numerical experiments are conducted in a Taichung City network, as shown in Figure 4, which includes 87 demand zones, 574 nodes and 1894 links. In these simulation experiments, 21,240 vehicles are generated within a 35-minutes period. The average travel time is 13.18 minutes, averaged stopped time is 3.80 minutes, and average travel distance is 3.97 km.

![FIGURE 4. The Taichung city network.](image)

**Sensitivity Analysis on the Bound, B**

In chance constrained programming, the objective is to minimize planned route costs, while ensuring that the probability of having a route duration in excess of B does not exceed a given threshold. The value of B represents a threshold and is a key factor in solving the formulation. Since there is no analytical method to determine B,
sensitivity analysis is adopted to generate the range of $B$. If the $B$ is too high, the constraint is inactive; if the $B$ is too low, no feasible solution could be found.

An average from-node-to-node travel time is calculated first, and an upper bound is approximated based on the number of nodes. Then, the upper bound is multiplied by a reduction factor ranging from 90% to 10%. The numerical results are summarized in Table 1. As shown in Table 1, a factor of 0.5 (0.7 when the number of demand nodes is equal to 10) is used to approximate a restriction on $B$.

### Table 1. Sensitivity Analysis of the value $B$

<table>
<thead>
<tr>
<th>Number of demand nodes</th>
<th>The value of $B$</th>
<th>route</th>
<th>Route Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>19</td>
<td>4.26×19=80.94</td>
<td>4,19, 8,11,13, 3, 6,18,17, 5,16,12,10, 9,14, 7,15, 2, 1</td>
<td>34.02</td>
</tr>
<tr>
<td>19</td>
<td>80.91×50%=40.45</td>
<td>4,19, 8,11,13, 3, 6,18,17, 5,16,12,10, 9,14, 7,15, 2, 1</td>
<td>34.02</td>
</tr>
<tr>
<td>19</td>
<td>80.91×40%=32.36</td>
<td>No Feasible Solution</td>
<td>--</td>
</tr>
<tr>
<td>15</td>
<td>4.00×15=60</td>
<td>4,15, 7,10, 5,14,13, 9, 3, 8,11, 6,12, 2, 1</td>
<td>29.42</td>
</tr>
<tr>
<td>15</td>
<td>60×50%=30</td>
<td>4,15, 7,10,13,14, 5, 3, 9, 8,11, 6,12, 2, 1</td>
<td>29.42</td>
</tr>
<tr>
<td>15</td>
<td>60×40%=24</td>
<td>No Feasible Solution</td>
<td>--</td>
</tr>
<tr>
<td>10</td>
<td>4.1753×10=41.753</td>
<td>2, 5, 9, 4, 7, 3,10, 8, 6, 1</td>
<td>28.26</td>
</tr>
<tr>
<td>10</td>
<td>41.753×70%=29.22</td>
<td>2, 5, 9, 4, 7, 3,10, 8, 6, 1</td>
<td>28.26</td>
</tr>
<tr>
<td>10</td>
<td>41.753×60%=25.05</td>
<td>No Feasible Solution</td>
<td>--</td>
</tr>
</tbody>
</table>

In these experiments, only one commercial vehicle is considered, and routing strategies are compared based on the commercial vehicle’s actual travel time. Experiments factors include:

1. Number of Demand Nodes

In order to illustrate the evaluation framework, three different demand nodes, including 10, 15, and 19 with a fixed depot are considered. All these demand nodes
are randomly picked up from CBD of the Taichung City Network. When the number of demand nodes increases, the number of sub-tour constraints increases exponentially. In order to consider the number of constraints and solution efficiency, as indicated in Table 2, the maximum number of demand nodes considered is set to 19.

2. Real-Time Dynamic Information

In these experiments, real-time travel time information is provided for a certain intervals, including 5 and 10 minutes. At each time interval, travel time on links as well as delays at nodes are estimated and the Floyd-Warshall algorithm is applied to calculate all-pairs shortest path and generates a travel time matrix.

Table 2. Number of Constraints in SVRP formulation

<table>
<thead>
<tr>
<th>Number of Demand Nodes</th>
<th>Decision Variables</th>
<th>Flow Conservation Constraints</th>
<th>Subtour Constraints</th>
<th>Time Constraints</th>
<th>Total Number of Constraints</th>
<th>Execution Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>5×5=25</td>
<td>10</td>
<td>10</td>
<td>1</td>
<td>21</td>
<td>0.64sec</td>
</tr>
<tr>
<td>10</td>
<td>10×10=100</td>
<td>20</td>
<td>627</td>
<td>1</td>
<td>648</td>
<td>4.65sec</td>
</tr>
<tr>
<td>15</td>
<td>15×15=225</td>
<td>30</td>
<td>16368</td>
<td>1</td>
<td>16399</td>
<td>19.23sec</td>
</tr>
<tr>
<td>18</td>
<td>18×18=324</td>
<td>36</td>
<td>155363</td>
<td>1</td>
<td>155400</td>
<td>4.6min</td>
</tr>
<tr>
<td>19</td>
<td>19×19=361</td>
<td>38</td>
<td>262124</td>
<td>1</td>
<td>262163</td>
<td>13.1min</td>
</tr>
</tbody>
</table>

Results Analysis

The results are summarized in Table 3, and vehicle routes are illustrated in Figure 5. The total route travel time for 10 demand nodes is about 65.80-71.80 minutes; for 15 demand nodes is about 68.61 ~ 73.00 minute; for 19 demand nodes is about 59.80 ~ 73.00 minute. Numerical experiments for different information types have similar trend, thus only the results from real-time information are discussed hereafter.

When the number of demand nodes is 10, the real-time information does not provide a positive change, and even worsens the vehicle’s total travel time. One possible reason might be that frequent updating pushes vehicles to take longer routes.

When the number of demand nodes is 15, real-time updating reduces travel time by about 20%. However, when updating routes for every 5 minutes, the total route
time gets worse.

When the number of demand nodes is 19, the route time is improved as the updating interval increases. In this case, the optimal updating interval is about 15 minutes. Although the result is not conclusive, the updating process needs to be carefully designed in order to take advantage of real-time traffic information.

Table 3. Travel Time Reduction and % of Improvement

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Travel Time (Mins)</th>
<th>% of Improvement</th>
<th>Scenario</th>
<th>Travel Time (Mins)</th>
<th>% of Improvement</th>
<th>Scenario</th>
<th>Travel Time (Mins)</th>
<th>% of Improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td>10-00-R</td>
<td>65.80</td>
<td></td>
<td>15-00-R</td>
<td>68.61</td>
<td></td>
<td>19-00-R</td>
<td>73.00</td>
<td></td>
</tr>
<tr>
<td>10-05-R</td>
<td>71.80</td>
<td>-9.11%</td>
<td>15-05-R</td>
<td>73.00</td>
<td>-6.09%</td>
<td>19-05-R</td>
<td>71.80</td>
<td>1.64%</td>
</tr>
<tr>
<td>10-10-R</td>
<td>65.80</td>
<td>0%</td>
<td>15-10-R</td>
<td>53.80</td>
<td>21.59%</td>
<td>19-10-R</td>
<td>67.00</td>
<td>8.22%</td>
</tr>
<tr>
<td>10-15-R</td>
<td>65.22</td>
<td>0.8%</td>
<td>15-15-R</td>
<td>53.80</td>
<td>21.59%</td>
<td>19-15-R</td>
<td>59.80</td>
<td>18.08%</td>
</tr>
</tbody>
</table>

19-00-R (Average travel time = 73.00mins)  
no real-time information

19-05-R (Average travel time = 71.80mins)  
real-time info. Interval: 5min

19-10-R (Average travel time = 67.00mins)  
real-time info. Interval: 10mins

19-15-R (Average travel time= 59.80mins)  
real-time info. Interval: 15mins
From all these experiments, several comparisons and conclusions are summarized as follows:

(1) In this framework, demand node sequence is much more important than paths between each pair neighboring nodes. The SVRP formulation provides a basic method to optimal routes under real-time traffic conditions; however, there are several factors that are difficult to operate during the calculation.

(2) Real-time information for updating routes could provide positive benefits, only with careful route generation.

CONCLUSIONS

In this paper, the SVRP formulation and solution is applied to study the effectiveness of real-time information as well as dynamic routing strategies in a realistic simulation environment. The SVRP formulation is solved through branch-and-bound technique by CPLEX. This approach provides a reliable and accurate way of solving SVRP problems, but the execution time increases exponentially as the number of demand nodes increase.

The core of the framework, DYNASMART, provides the capabilities of traffic simulation and route assignment. The framework provides a practical tool for the evaluation of vehicle routing strategies under real-time information. This capability is necessary to evaluate phenomena where time-variation is essential, including dynamic fleet management and real-time information systems.

The numerical results indicate that real-time information could provide positive benefit only under careful consideration and design; however, interval of updating
routes might lead to worse results due to overheads in route changing. Possible development in the future includes route generation and improvement process and time-dependent issue consideration.

ACKNOWLEDGEMENT
This paper is based on work supported by National Science Council, Taiwan, R.O.C. under the project NSC89-2416-H-035-010. Of course, the author is solely responsible for the contents of this paper.

REFERENCES