

Multi-Constraints and Single Objective Based Optimum Routes Planning for Assisted Evacuation

A Geographic Information System Based Solution and Simulation

Md. Imran Hossain

*Institute for Applied Computer Science, University of the Bundeswehr Munich,
Werner-Heisenberg-Weg 39, 85577 Neubiberg, Germany*

1 RESEARCH PROBLEM

With the advancement of modern technologies it is now more or less possible to predict almost all kind of natural and manmade disasters in terms of their time of occurrence, intensity and geographic area of occurrence. However, recent large natural and anthropogenic disasters have clearly shown various shortcomings and failures in existing technologies for efficient emergency response especially in the domain of evacuation (Konečný, Zlatanova and Bandrova, 2010). Depending on the magnitude, especially when a massive destruction is expected for a forthcoming disaster, evacuations sometime become so obvious to minimize the casualties. When an evacuation becomes obvious, the responsible authorities usually announce the event through different media and possibly with escape routes and directions. Thus, in the event of evacuation, people who have their own vehicle or have good access to the available transport modes can evacuate by themselves. On the other hand, there are always special groups of people who are subject to severe mobility restrictions in terms of lack of personal transportation, limited financial resources, unfamiliarity with the area and its road network, physical and mental disabilities, language barrier etc. (Zimmerman, Brodesky and Karp, 2007). These groups of people are therefore at greatest risk of casualties. The responsible authorities (public safety agencies, police department etc.) for evacuation provide special evacuation units (vehicles) to collect and shift those special groups to a safe place which is called herein as the assisted evacuation.

The route plan for each evacuation unit has significant effects on the efficiency of such assisted evacuation. The contemporary manual route planning with unknown spatial evacuee distribution hinders the performance of assisted evacuation in many folds. First of all, the evacuation units have to go through all the streets of a given area of evacuation which usually lead to a substantial waste of time and therefore become very inefficient

especially when the evacuation is bounded by huge time pressure. Secondly, the manual process is unable to give estimation for the required/optimum number of evacuation units to cover all the evacuees who need assistance. And finally it cannot provide estimation for evacuees to be covered under certain time and resource constraints. Therefore, with a known spatial distribution of the evacuees, automatic dynamic optimized route plans for the evacuation units would certainly preside over the any manual interventions in this case.

An incident manager, under any circumstances, would be interested to cover all the evacuees of an area which is under disaster threat. But this might not happen in reality as the performance of assisted evacuation of an area depends on the route plan of each evacuation unit together with at least three major factors or variables: 1) Total available time (T): the time segment between the announcement of an evacuation and the actual disaster event. 2) Total available evacuation units (U) and 3) Number of evacuees (E): the number of the evacuees who need assistance. Therefore, a decision support system that can deliver the optimized dynamic route plans for all the evacuation units by fixing any two variables/factors and keeping the third as a goal would enable the incident manager for estimating the required resources and to take the right decision in a given evacuation scenario. Along with the optimized route plans the decision support system should answer the following questions as well.

- 1) How many evacuees (E) could be evacuated under certain time (T) and resource (U) constraints?
- 2) How many evacuation units (U) would be required to evacuate a certain number of evacuees (E) under a certain time (T) constraint?
- 3) How long (T) would it take to evacuate certain amount of evacuees (E) with certain number of evacuation units (U)?

This research project is therefore intended to develop such kind of decision support system (DSS). The DSS would be further tested, verified and validated by a suitable simulation technology.

2 OUTLINE OF OBJECTIVES

The overall aim of this research is to design, build and validate a decision support system that can produce optimal dynamic route plans for multiple evacuation units involved in the assisted evacuation with multiple constraints and a single objective. To achieve this aim the following research objectives are formulated.

- Objective 1: To estimate the spatio-temporal distribution of the evacuees who need assistance.
- Objective 2: To divide a geographic area defined by a set of geographic features (buildings in this case) into multiple regions in a way that each region is consists of almost equal number of evacuees.
- Objective 3: To estimate time required for evacuating different type of evacuees considering the traffic situation and surrounding environment.
- Objective 4: To develop dynamic routing algorithm for optimum path generation that further allows routing during run time.
- Objective 5: To design and build a decision support system with the output of all previous four objectives.
- Objective 6: To simulate some disaster cases with appropriate simulation technology/ies to test, verify and validate the decision support system.

3 STATE OF THE ART

A spatial decision support system is an interactive, computer-based system designed to support a user or a group of users in achieving greater effectiveness in decision-making while solving a semi-structured (not completely programmable) spatial decision problem (Malczewski 1999). There are quite a large number of DSSs exist in the domain of Geographic Information System (GIS). However, the author did not find any decision support system that provides exact solutions to the problem stated in the problem statement part (section 1). However, quite a number of literatures related to the objectives, especially objective no. 1 to 4 are already available. Therefore, the state of the art, herewith, is formulated according to the different objectives of this research and is given with the following subsections.

3.1 Spatio-Temporal Distribution of Evacuees Who Need Assistance

Ahola et al. (2007) have developed a spatio-temporal population model to support risk assessment and damage analysis for Finnish Fire and Rescue Services and the Finnish Defence Forces. Their model uses a basic population and workplace dataset maintained by the Helsinki Metropolitan Area Council. With the model the authors prepare population density map for day and night time for a specific area.

Ural, Hussain and Shan (2011) have tried to map the spatial distribution of population in a different way mainly using a combination of aerial imagery and GIS data. In their work they have extracted the buildings from aerial imagery and then classified those through City Zoning maps. Additional ancillary geo-data has been used to filter out the utility buildings. Finally, census block data has been disaggregated and linked to the individual building.

Freire (2010) has used a dasymetric mapping approach to refine population distribution in Portugal. The author has calculated the maximum day time and night time population for each 25 m grid cell of a raster map.

It is clear that different approaches and techniques are already available mainly for mapping the spatial distribution of population. The temporal aspects are considered in few cases but with a very coarse temporal resolution. However, in this research spatio-temporal distribution of the evacuees who need assistance, need to be known. This could be achieved through either enrichment and modification of the available methodologies or development of completely new methodology.

3.2 Regionalization/Zoning Systems

Automated zone design (AZD) or regionalisation is a technique for which Shortt (Thrift and Kitchin, 2009) has given the overview of its concept, terminology and methods. AZD is an umbrella term for quite a number of approaches to create zones from a set of basic building blocks following given criteria. Among the automated zone design algorithms automated zone design procedure (AZP) is the most popular and widely used one. It was introduced by Openshaw and Baxter (1977). The AZP has been enhanced by Openshaw and Rao (1994), Alvanides (2000) and Alvanides et al (2002). Cockings et. al. (2011) used automated zone design techniques to dynamically maintain existing zoning systems. There are also a lot of other application of AZP algorithm such as climate zoning, location optimization and many more. The AZP algorithm

iteratively combines and recombines sets of blocks in order to create output zones which are optimised based on a set of pre-specified design criteria (Openshaw and Rao, 1994).

AZP is not applicable to the task defined in objective 2 as firstly, AZP is applicable only to continuous and connected feature sets whereas in our case continuous and discrete feature sets must be treated. Secondly, in AZP the geometric structure and thematic attributes of the input building blocks are destroyed to form a new zone out of them. This should not be allowed in the present research work. Also it is required in our approach that the bounding polygon of each region must not overlap with any other region to offer a distinct separate area for each evacuation unit.

3.3 Time Estimation for Evacuation

The evacuation time requirement is expected to vary according to the type of evacuees who need assistance and their surrounding environment. For example the required time for evacuating a physically disabled evacuee who lives at the 10th floor would be much higher than an evacuee who just doesn't have transportation access and resides at a single storied building. A model has to be developed in this research that can provide information on required time for a specific type of evacuee considering the surrounding environment. Unfortunately, no literature has been found that present such a model. Therefore, this type of model has to be built from the scratch.

3.3 Dynamic and Optimum Routing Algorithms

Hundreds of routing algorithms are available nowadays for calculating paths between two or more points of interest. Laporte (1992) provides a general wide overview and classification of the vehicle routing algorithms. Most of them till date are static in nature means the underlying data are known in advance. On the other hand, routing algorithms are designed in a way that it can provide routed between the points of interest at a minimum cost, generally the total travel time or the total travelled distance.

In the premise of Dynamic Vehicle Routing Problems (DVRPs) new orders dynamically arrive when the vehicles have already started executing their tours, which consequently have to be re-planned at run time in order to include these new orders (Montemanni et al., 2003).

The DSS to be built in this research is expected to provide routes for each evacuation unit involved

in the assisted evacuation in a way that instead of shortest or fastest path, it can produce an optimized path to serve all the evacuee of the defined territory of an evacuation unit in an optimized way. In addition, the routing algorithm should support the DVRP as spatial distribution of the evacuees could change over time.

4 STAGE OF THE RESEARCH

The authors at this stage successfully achieved only objective number 2. An algorithm for segmenting a geographic area defined by a set of geographic feature set into equitable regions has been developed, implemented and published in the 17th AGILE Conference on Geographic Information Science (Hossain and Reinhardt, 2014). A brief summary of the work is given below.

4.1 the Task

A geographic area G defined by a feature set consisting of n features with a numeric attribute A has to be completely divided into N ($N \in \mathbb{N} \mid 2 \leq N \leq n$) number of subsets/regions based on 3 criteria.

Input:

- Geographic area $G = \{f_n \mid f_n \in F \text{ (set of features)}, f_n \text{ has a numeric attribute } A\}$
- N ($N \in \mathbb{N} \mid 2 \leq N \leq n$) = number of required subsets of G , N has to be defined by the user.

Output:

- N number of subsets R_n (subsets/regions)

Criteria:

- 1) Region cannot be formed with splitted feature means a feature of a region is not allowed to be in a form like $f_i/m \mid m \in \mathbb{N}$.
- 2) The sum of $|A|$ ($|A|$ is the value of attribute A) of any region defined herein with $O(R_i) = T \pm d$
- 3) The bounding polygon of any subset $BNDline(R_i)$ do not overlap with the bounding polygon of any other.

The value of T is calculated by equation 1 and the value of d is an element of set D . The value of d can ranges from 0 to the maximum value of $|A|$ of a given feature set G (equation 2).

$$T = \frac{\sum_{f=1}^n |A|(G)}{N} \quad (1)$$

$$d \in D = \{q \in \mathbb{Q} \mid 0 \leq q < MAX(|A|(G))\} \quad (2)$$

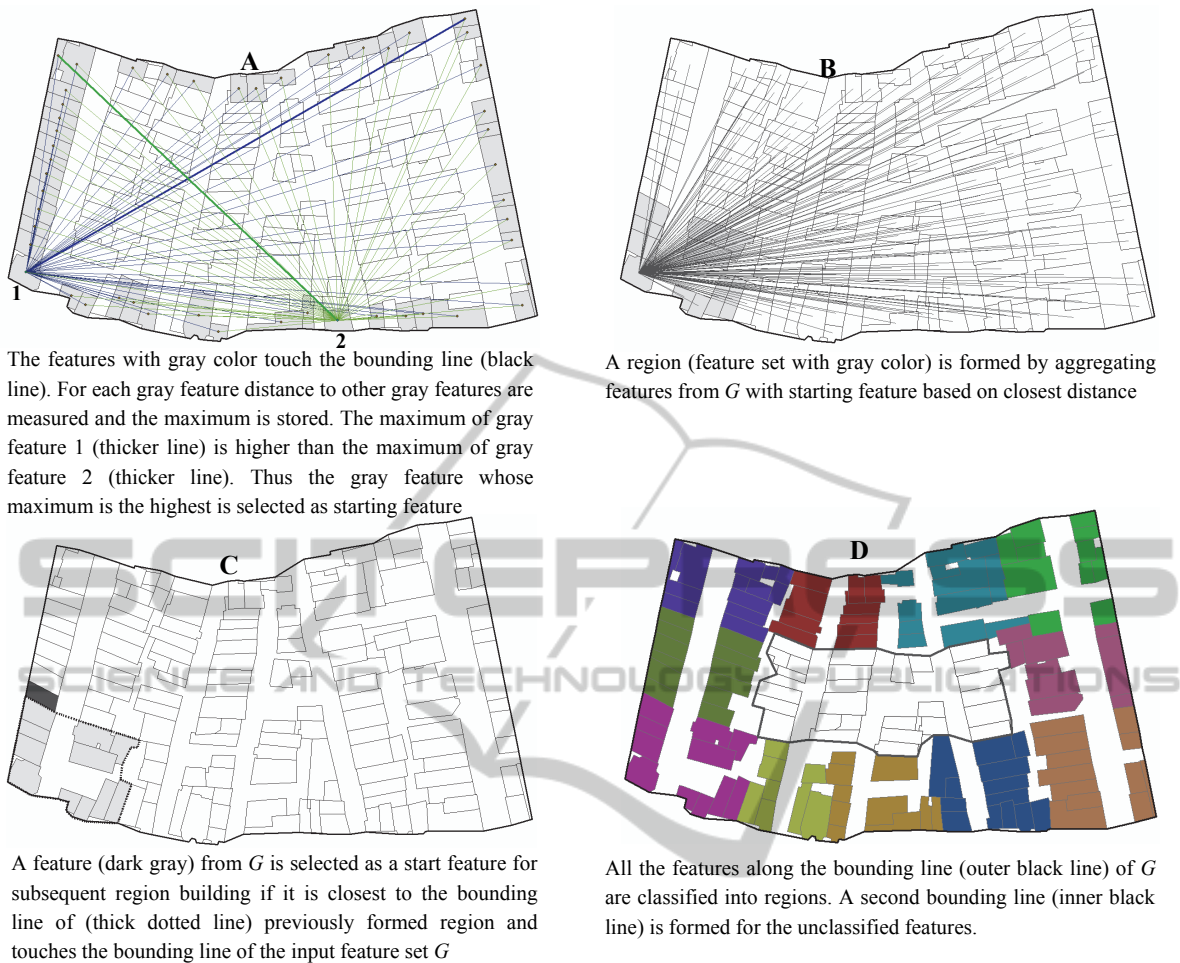


Figure 1: Visual illustration of different steps of the algorithm.

In general, the algorithm prioritizes forming regions along the bounding line $BNDline(G)$ of the input feature set G . This approach prevents features being unclassified and also prevent big differences among the regions. A region R_i is formed by grouping features around the bounding line until $O(R_i) = T \pm d$. Once no region formation is possible along the $BNDline(G)$, another bounding line is created for the features which are not classified into regions and regions are again formed along the new bounding line. This process continues until $N-1$ regions are formed. The N^{th} region is formed with remaining unclassified features after formation of $N-1^{th}$ region and consequently it's possible that the sum of $|A|$ may not be within $T \pm d$ in this case.

4.2 Steps of the Algorithm

The algorithm is described in more detail through the following steps.

Step 1: Objective Function Calculation

Objective function returns the value of T on which each region is formed. T is calculated through equation 1.

Step 2: Selection of the Starting Feature for the First Region

The starting feature for the first region is selected by two criteria. Firstly, it has to be along the $BNDline(G)$ and secondly it has to be located in an appropriate corner of G . Therefore the starting feature is selected by firstly making an array of features that touches the $BNDline(G)$. Secondly a feature is picked up from that array and distances are calculated from that feature to all other features of that array. The maximum distance is then stored with each picked up feature. This process is carried out for all features in the array. Finally, the feature that has the maximum distance value compared to

other features in the array is selected as a starting feature for the first region formation (fig. 1A).

Step 3: Formation of the First Region

At the beginning the first region R_1 is formed only with the starting feature. Then the region is grown by grouping features from G on the basis of minimum distance, which means a feature from G is allowed to be grouped with the starting feature if the distance between them is a minimum compared to the distance of other features in G (fig. 1B). This grouping or region building is continued until $O(R_i) = T \pm d$ criteria is fulfilled. Since a feature in G is not allowed to divide according to the underlying data model, it is only possible to completely include or exclude a feature to a region. Which means the feature cannot be sliced. So, $O(R_i)$ cannot always be exactly equal to T . The maximum possible deviation of $O(R_i)$ with T for R_1 to R_{N-1} will be thus the maximum value of $|A|$ of any given G .

Once a region R_i is formed, a static variable $StatN$ is updated with the number of region formed and the feature set on which the process will be continued is obtained by $G - R_i$. The process terminates and goes out of scope when $N-1 = StatN$. For example, if 3 regions are expected and 2 regions have already been completed then remaining features of G automatically form a region and the process goes out of scope.

Step 4: Start Feature Selection for the Subsequent Regions

As stated earlier, the algorithm prioritizes forming regions along the bounding line $BNDline(G)$ of the input feature set G . Therefore, a start feature for any subsequent region R_{i+1} should be located next to the former region R_i and also should touch the $BNDline(G)$ (fig. 1C). These are two simple criteria for selecting a start feature for any subsequent region building.

Step 5: Repetition

Step 3 to 4 are repeated until no start feature is returned by step 4 and the required number of regions is still not achieved. A null feature return by step 4 means all the features along the bounding line of G are classified into regions. If this is the case, a new bounding line is created for the set of non-classified features (fig. 1D). The $BNDline(G)$ which is created in step2 is replaced by the new bounding line and the process starts continuing from step 2.

4.3 Implementation and Results

The algorithm presented in section 4.2 has been implemented using c# programming language and ArcObjects library of ESRI. Figure 2 and 3 show the result of 2 examples of an application of the implemented algorithm. Each feature (polygon) in both figures represents residential buildings and has an attribute called population (no. of residents). The maximum value of d of the input feature set was 21.

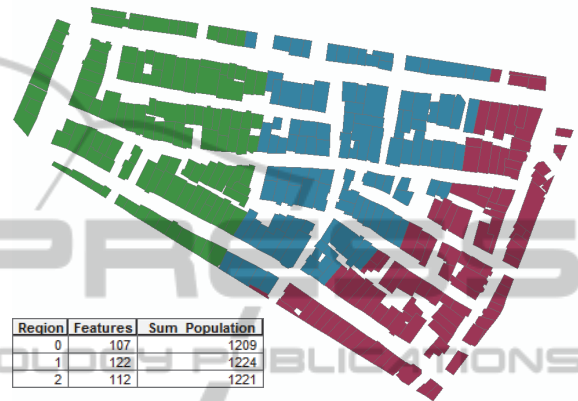


Figure 2: Input feature set divided into 3 equitable regions.

In figure 2, the expected number of equitable regions was 3 based on the population attribute which means the feature set has to be divided into 3 non-overlapping regions so that the total population for each region remains approximately equal.

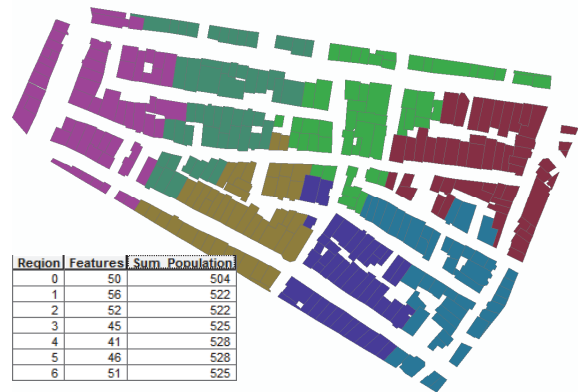


Figure 3: Input feature set divided into 7 equitable regions.

In figure 3 the expected region number was 7. Both figures show a distinct division of the feature set into regions. None of the region in both figure overlap with others. The important point to be noted here is that region no.0 in both figures differs significantly from other regions in terms of total population and the difference goes beyond the $MAX(d)$ in figure 7. The differences among other regions are minimal and within $MAX(d)$.

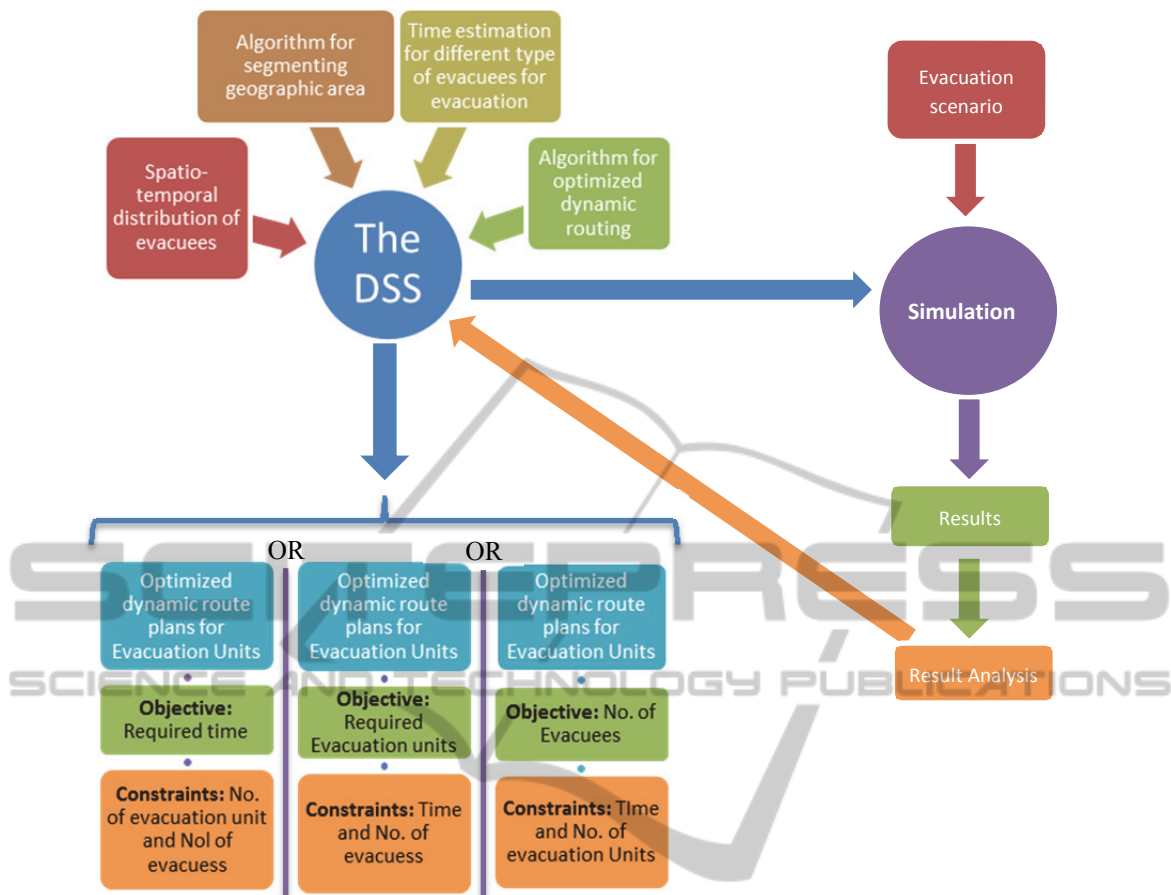


Figure 4: A gross methodology of the research.

Region 0 is in fact the last region formed with the remaining feature set once $N-1$ regions are formed. If the other regions formed with a positive value of d (section 3, step 3) then the effect goes on to the last N^{th} region (region 0) which is forced to be formed with a total value deduced by the cumulative positive d of the former regions. Thus only the N^{th} region's $O(R_n)$ may not be equal to $T \pm d$. The maximum difference between the last region's $O(R_n)$ with other regions $O(R_i)$ is thus expected to be higher with the increased no. of regions. However, this problem can be solved with a constraint that two consecutive regions should form with $+d$ and $-d$ simultaneously which restricts region formation with always $+d$ or $-d$.

5 METHODOLOGY

The methodology of this research is presented by figure 4. The DSS which is the core of the present research is foreseen to be composed of four different components. The first component is a model which

would provide the spatio-temporal distribution of the evacuees who need evacuation assistance. The second component is an algorithm by which a given geographic area would be divided into multiple equal regions in terms of the number of evacuees and their corresponding required evacuation time to assign each evacuation unit to a region. Development of the second component is already done for which a brief summery is given in the section 4. The third component is a model to estimate the required time for evacuating a specific type of evacuee considering his/her surrounding environment. And the fourth component is again an algorithm which would provide dynamic route plan for each evacuation unit with optimized path.

The outcome/usage of the DSS is shown by the thick blue downward arrow in figure 4. Three possible outcomes are shown here. An incident manager can go for any one among the possible three. All the outcomes have a common feature which is the optimized dynamic route plans for the evacuation units. Along with this, an incident manager can fix two constraints at a time and can get a decision regarding an objective. For example if

no. of evacuation unit and the no. of evacuees are fixed then the incident manager will get as outputs the required time and the route plans.

Once the DSS is build, a suitable simulation framework would be created for testing, validation and verification of the DSS. Decision regarding the technological aspects behind the simulation is not yet decided. It might be an agent based simulation, statistical simulation or any other depending on the suitability and purpose of the DSS.

Some evacuation scenarios would then be simulated by combining the DSS with the simulation framework. The result of the simulation would be analysed. Any drawbacks or shortcoming that may become identified with the analysis will then be adjusted in the DSS (the components of the DSS).

6 EXPECTED OUTCOME

The main outcome of this research is a multiple constraints based decision support system for a single evacuation objective supported by optimal dynamic route plans for multiple evacuation units involved in the assisted evacuation. With the decision support system an incident manager, among the three variables: time, resources and evacuees, could make estimation for one variable while fixing the other two, supported by optimized dynamic routing plans for the evacuation units. Moreover, this research would create some further by-products which are listed below.

1) Methodology for estimating the spatio-temporal distribution of the evacuees who need evacuation assistance.

2) An algorithm for segmenting a geographic area into equitable regions

3) Methodology for estimating the time requirement for evacuating different types of evacuees considering the traffic situation and surrounding environment.

4) An advanced algorithm for optimized routing. The routing algorithm is also expected to be dynamic which means it can provide alternative updated route plans during run time.

5) A simulation framework for the testing, varifying and validation of the DSS with some disaster cases.

REFERENCES

Ahola, T., Virrantaus, K., Krisp, J. and Hunter, G. (2007). A spatio-temporal population model to support risk assessment and damage analysis for decision-making.

- International Journal of Geographical Information Science*, 21(8), pp.935--953.
- Alvanides, S. (2000). *Zone Design Methods for Application in Human Geography*. Ph.D. School of Geography, University of Leeds.
- Alvanides, S. Openshaw and P. Rees (2002). Designing your own geographies. *The Census Data System*, pp. 47--65.
- Cockings, S., Harfoot, A., Martin, D. and Hornby, D. (2011). Maintaining existing zoning systems using automated zone-design techniques: methods for creating the 2011 Census output geographies for England and Wales. *Environment and Planning-Part A*, 43(10), p.2399.
- Freire, S. (2010). Modeling of Spatiotemporal Distribution of Urban Population at High Resolution – Value for Risk Assessment and Emergency Management. In: M. Konecny, S. Zlatanova and L. Bandrova, ed., *Geographic Information and Cartography for Risk and Crisis Management-Towards Better Solutions*, 1st ed. Berlin: Springer-Verlag Berlin Heidelberg, pp.52-67.
- Hossain, M. and Reinhardt, W. (2014). An algorithm for segmenting a feature set into equitable regions. In: *Connecting a Digital Europe through Location and Place*. Castellón: Association of Geographic Information Laboratories for Europe (AGILE).
- Konečný, M., Zlatanova, S. and Bandrova, T. (2010). *Geographic information and cartography for risk and crises management*. 1st ed. Heidelberg: Springer Verlag.
- Laporte, G. (1992). The vehicle routing problem: An overview of exact and approximate algorithms. *European Journal of Operational Research*, 59(3), pp.345--358.
- Malczewsky, J. (1999). *GIS and Multi-Criteria Decision Analysis*, New York: Wiley.
- Montemanni, R., Gambardella, L., Rizzoli, A. and Donati, A. (2003). A new algorithm for a dynamic vehicle routing problem based on ant colony system. 1(1), pp.27--30.
- Openshaw, S. and Baxter, R. (1977). Algorithm 3: a procedure to generate pseudo-random aggregations of N zones into M zones, where M is less than N. *Environment and Planning A*, 9(6), pp.1423--1428.
- Openshaw, S. and Rao, L. (1994). *Re-engineering 1991 census geography*. 1st ed. Leeds: School of Geography, University of Leeds.
- Thrift, N. and Kitchin, R. (2009). *International encyclopedia of human geography*. 1st ed. Amsterdam: Elsevier.
- Ural, S., Hussain, E. and Shan, J. (2011). Building population mapping with aerial imagery and GIS data. *International Journal of Applied Earth Observation and Geoinformation*, 13(6), pp.841--852.
- Zimmerman, C., Brodesky, R. and Karp, J. (2007). *Using highways for no-notice evacuations*. 1st ed. Washington, D.C.: Federal Highway Administration, Office of Operations.