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A Genetic Algorithm Approach to the Frequency Assignment Problem on VHF Network of SPIDER System

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Abstract

A frequency assignment problem on time division duplex system is considered. Republic of Korea Army (ROKA) has been establishing an infrastructure of tactical communication (SPIDER) system for next generation and it will be a core network structure of system. VHF system is the backbone network of SPIDER, that performs transmission of data such as voice, text and images. So, it is a significant problem finding the frequency assignment with no interference under very restricted resource environment. With a given arbitrary configuration of communications network, we find a feasible solution that guarantees communication without interference between sites and relay stations. We formulate a frequency assignment problem as an Integer Programming model, which has NP-hard complexity. To find the assignment results within a reasonable time, we take a genetic algorithm approach which represents the solution structure with available frequency order, and develop a genetic operation strategies. Computational result shows that the network configuration of SPIDER can be solved efficiently within a very short time.

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1. Introduction

Republic of Korea Army (ROKA) has been structuring an infrastructure of tactical communication system for the next generation, SPIDER, and it will be a core infrastructure of the tactical (Command, Control, Communication, Computer and Intelligence) systems. The communication system that has been operated by ROKA has a point-to-point mode, so, the survivability can not be ensured when an edge is disconnected in the network. Furthermore, when a critical edge in network system is down, the possibility of failure on network system increases. Therefore, ROKA considers the substitutions of network configuration of next generation communication system to ensure the survivability and communication under large amount of data traffic such as voice, text and image.

The physical configuration of SPIDER shows a grid type network. The sites are connected with adjacent sites or relay stations. VHF (Very High Frequency) system will play role of a backbone network in SPIDER to transmit of data. To overcome rugged terrain features, relay stations are ordinarily positioned between communication sites since VHF system has LOS (Line Of Sight) communication property. The end users have to connect their terminals to the closest node for communication. Figure 1 shows a typical representation of SPIDER network configuration.

ROKA decided TD (Time division Duplex) system as VHF system for SPIDER. TD system uses just one channel between two transmitters for communication. It divides time into very short intervals (seconds) and transmits and receives data in turn.

When we operate TD system, we must consider far-site and co-site interference for communication. Far-site interference is the noise that comes from the none-matched TD systems located on other sites. Usually, multiple number of systems is operated on one site and/or relay station. Therefore, a receiver takes electric waves from not only a matched system but also other non-matched systems. Co-site interference is the noise that comes from other transmitters located on the same site. Its noise is generally stronger than that of far-site interference. When we

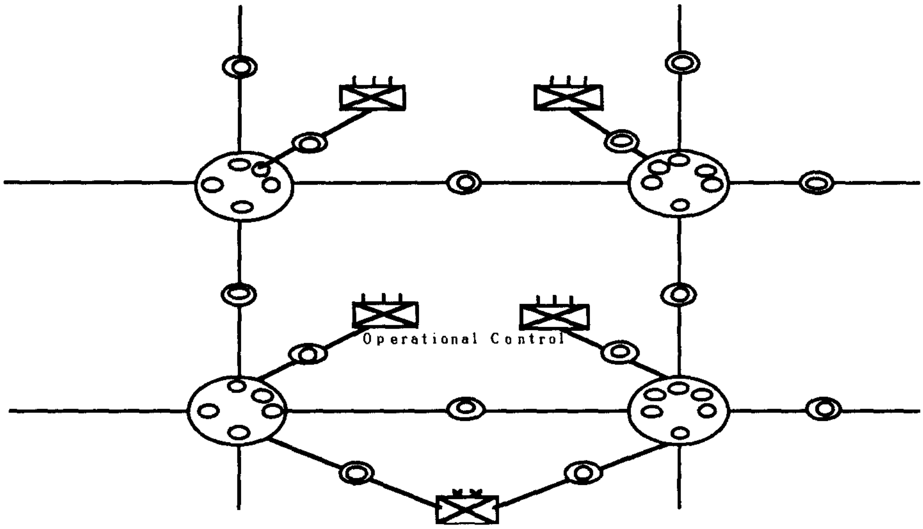


Figure 1. Typical Configuration of SPIDER system

handle two types of interference, we consider only co-site interference because we can exclude far-site interference by providing enough frequency separation when we assign frequencies as input data set. Figure 2 shows three kinds of interference. In Figure 2, auto-interference is occurred only in the FD (Frequency division Duplex) system. FD system uses 2 channels for communication between sites. Therefore, we have to consider auto-interference separation when we allocate frequency on FD system.

The radio spectrum is already becoming limited resource, so it is vital to manage frequency effectively. As the Figure 3 shows, the available frequency is very small amount and is spread on the 3 bands. Each band is separated enough to exclude co-site interference. And the scope of available frequency is not consecutive in a band because the rest of frequency is already allocated for the commercial or other purpose. It is difficult to find a feasible solution under wide interference separation and insufficient available frequency band. Thus, in this paper, we will make effort to find a feasible solution that excludes interference.

Even though TD system for next generation has frequency hopping ability, we did not consider the function because of limited frequency resources. We can not support division size VHF network using the frequency hopping function.

Many researchers have studied frequency assignment problem for several decades.

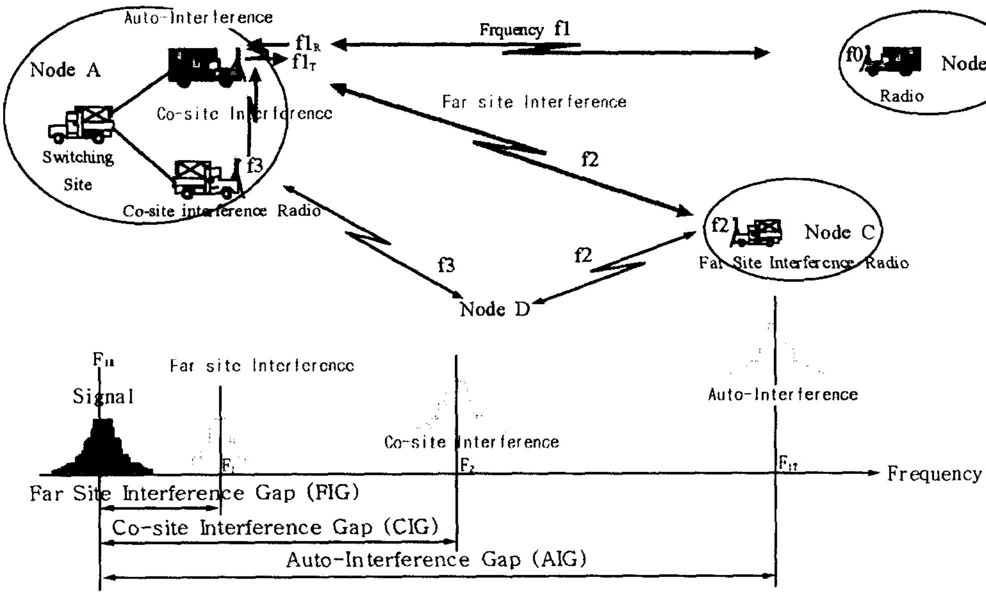


Figure 2. Three kinds of interference

They developed and found algorithms on specific assignment problem. Hurley and Smith[8], Knalmann[11] et al. presented the simulated annealing algorithm on frequency assignment problems. Quellmalz[16] et al. also studied simulated annealing algorithm and compared the results with that of the exact algorithm. Smith used a genetic algorithm for the channel assignment problem. Castelino et al.[2] applied tabu search algorithm for frequency assignment and compared the results with that obtained by parallel genetic algorithm. Other researchers applied Kalman-filter method[12], neural network[18] for the channel assignment problem. The measures they consider include the span, the order, the weighting of constraints and the sum of the positive discrepancies of the assignment. Generally, they permitted reuse of frequency, but the reuse is not permitted in our research. For the other approaches of frequency assignment problem, see the references [7] and [13].

We formulate FAP (Frequency Assignment Problem) as an Integer Programming model and describe the computational complexity of FAP in section 2. We apply the genetic algorithm to solve the problem within a reasonable time. The representation of solution structure, initial population generation, genetic operations such as crossover and mutation, and selection strategies are provided in section 3. The computational results with SPIDER system and the analysis of results are given in section 4. Finally, we give the concluding remarks in section 5.

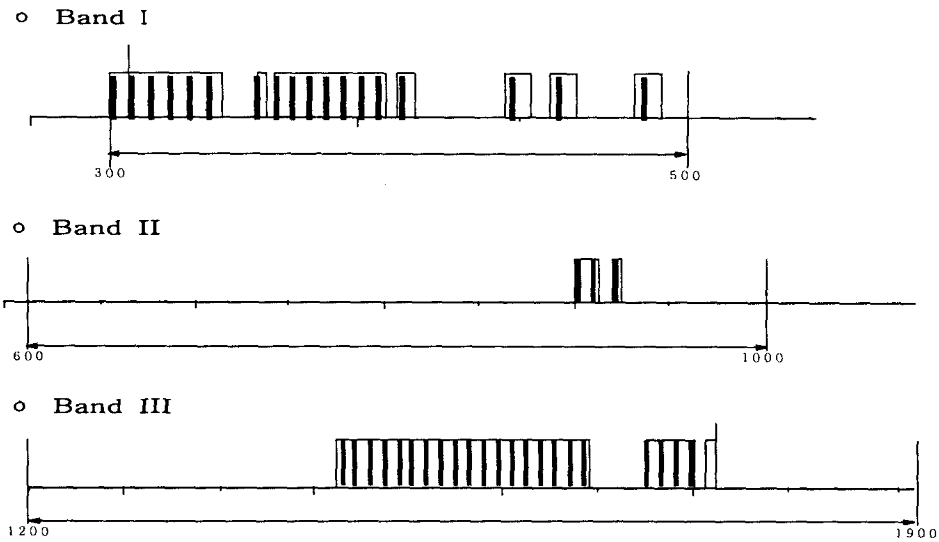


Figure 3. The available frequency scope

(Band values are imaginary number because of security)

2. Problem Description and Formulation

VHF system can be mapped onto the network system. Each site and relay station is regarded as node in the network. The edge of network is generated when data transmission and reception should be performed between two nodes. Therefore, we can construct network configuration whatever the tactical communication requirement happens.

To describe Frequency Assignment Problem (FAP) as an Integer Programming model, let's define the following notations.

V : The set of nodes

A : The set of edges in network

F : The set of available frequencies

x_{ij}^{k} : The binary decision variable,

if edge *(i,j)* is allocated by the *kth* frequency $x_{ij}^{k}=1$

otherwise, $x_{ij}^{k}=0$

α : The separation of frequency for co-site interference

β^k : The value of frequency k

γ_{ij}^k : The cost for a frequency k on the edge (i,j)

(FAP1)

$$\min \sum_{(i,j)\in A} \gamma_{ij}^k x_{ij}^k \tag{1}$$

$$s.t \quad \sum_{(i,j)\in A} x_{ij}^k \le 1 \qquad \text{for all } k \in F \tag{2}$$

$$\sum_{k\in F} x_{ij}^k = 1 \qquad \text{for all } (i,j)\in A \tag{3}$$

$$\left|\sum_{k\in F}\beta^k x_{ij}^k - \sum_{k\in F}\beta^k x_{il}^k\right| \ge \alpha \qquad \text{for all } i\in V \ (i,j)\in A \ (i,l)\in A \textit{ where } j\ne l \tag{4}$$

$$x_{ij}^k \in \{0,1\} \quad (i,j)\in A \quad k\in F \qquad \text{for all} \tag{5}$$

Constraints (4) are divided into two constraints set (6) and (7).

$$\sum_{k\in F}\beta^k x_{ij}^k - \sum_{k\in F}\beta^k x_{il}^k \ge \alpha \quad i\in V \ (i,j)\in A \ (i,l)\in A \textit{ where } j\ne l \qquad \text{for all} \tag{6}$$

$$\sum_{k\in F}\beta^k x_{il}^k - \sum_{k\in F}\beta^k x_{ij}^k \le \alpha \quad i\in V \ (i,j)\in A \ (i,l)\in A \textit{ where } j\ne l \qquad \text{for all} \tag{7}$$

Therefore FAP1 can be transformed into FAP as shown below.

(FAP)

min (1)

s.t (2),(3),(6),(7),(5).

Constraints (2) imply that a candidate of frequency should be used at most one time. Constraints (3) say that only one frequency should be allocated on an edge. Constraints (6) and (7) represent that co-site interference should be excluded between two nodes. When we need to forbid a specific frequency to allocate it on a specific edge, we set constant γ_{ij}^k to be a large number to the objective function. In this paper, we set all γ_{ij}^ks to be 1. It means that we have interest to find only a feasible solution.

The computational complexity of FAP is known to be NP-hard [2]. Hence, there is no known algorithm that can generate a guaranteed optimal solution in an execution time that may be expressed as a finite polynomial of the problem dimension. So, we try to find the solution by a genetic algorithm. For the detailed concept of computational complexity, see the references [5], [8] and [15].

3. Genetic Algorithm for FAP

3.1 Introduction

Genetic algorithm (GA) is biologically inspired search method borrows mechanisms of inheritance to find solutions [10]. GA is a general purpose search method that can be used to provide heuristic solutions to hard combinatorial optimization problems. GA searches a problem space with a population of structure and selects structures for continued search based on their performance. Each structure decodes to form a point in the problem space in the context of optimization problems [4].

GA has achieved successfully in field of many industrial engineering and management science, especially job-shop scheduling, keyboard configuration design, optimization and pipeline systems, traveling salesman problem, and multi-vehicle routing problem[1, 3, 14, 17, 19]. Therefore, GA is a reliable approach to obtain solutions in hard combinatorial optimization problems.

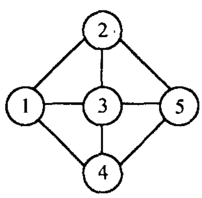
GA repeats the same procedure to get solution through generations. However, it has a flexible structure that can change the procedure and adopts various strategies according to the characteristic of the problem. So, researchers have developed many strategies and methods to get good solutions in a short time. The solution of one generation evolves by the crossover and mutation operations as the generation proceeds. To make the implementation of GA on a specific problem, first of all, we have to represent the problem solutions ("genetic encoding") that can be manipulated (through some sort of "crossover" or "mutation") to yield other candidate solutions to the problem. Second, acting on an initial population, these transformations create the next "generation" of candidate solutions. Third, calculation of the objective function for each candidate solution supplies a measure of "fitness" which affects its likelihood of leaving surviving offspring in the next generation. "Selection pressure" is the tendency toward the survival of the fittest; high selection pressure means low probability of the survival of the less fit. For the detailed concept of GA, see the references [1, 14, 15, 17].

The general procedure of GA is shown as below.

```
Begin
t ← 0
P(t) Initialization(Generation of initial population)
Evaluation of P(t)
While(not satisfy the condition of termination) do
  Begin
  t ← t + 1
  Selection P(t) from P(t-1)
  Genetic operations(Crossover and mutation)
  Evaluation of P(t)
  End
End
```

3.2 Representation of Solution Structure

To represent a solution structure, we give orders to the edges and frequencies according to the arbitrary reasonable criterion. In this paper, we establish order of numbers according to the sequence criterion. The sequence criterion is a method to determine the orders based on the network configuration matrix. We represent a VHF network by a binary matrix, in which an edge *(i,j)* has value 1 if the edge between node *i* and node *j* is connected. Let's assume that a network configuration is given as Figure 4. Then the binary matrix can represent the following network.



$$
\mathit{NODE}\quad
\begin{array}{c}
\\ 1 \\ 2 \\ 3 \\ 4 \\ 5
\end{array}
\begin{array}{c}
\begin{array}{ccccc} 1 & 2 & 3 & 4 & 5 \end{array} \\
\begin{pmatrix}
0 & 1 & 1 & 1 & 0 \\
1 & 0 & 1 & 0 & 1 \\
1 & 1 & 0 & 1 & 1 \\
1 & 0 & 1 & 0 & 1 \\
0 & 1 & 1 & 1 & 0
\end{pmatrix}
\end{array}
$$

Figure 4. Representation of network configuration

In Figure 4, edge (1,2) becomes the 1^{st} order and edge (1,3) has 2^{nd} order, and edge (1, 4) has 3^{rd} order. The remaining edges have their orders as the same way. The order based representation for a network enables us to construct the solution in genetic algorithm.

For FAP, a vector structure can be represented for the frequency assignment in the network. For example, the solution structure of (1,4,7,5) means 1^{st} frequency candidate is allocated on the 1^{st} edge and 4^{th} frequency candidate is allocated on the 2^{nd} edge. As the same way, 7^{th} and 5^{th} frequency candidates are allocated on the 3^{rd} and 4^{th} edges, respectively. As it is stated above, the number of frequencies should be great than that of edges to maintain feasibility. So, we generate the solution candidate in the full available space of frequency set.

3.3 Generation of initial population and population size

The proper size of initial population is important to perform genetic algorithm to solve the problem successfully arising in many fields of industrial engineering. We set the population size to be 100 and generate the initial population with random number generation as explained in section 3.2. Every locus(element) in the string(solution) should be represented differently from the other locus. In other words, a solution structure has solution length same as the number of edges in the network and must have the different elements. For example, if the number of edges and available frequencies are 5 and 7, respectively, a solution (1, 3, 4, 5, 7) is acceptable, but solution (1, 3, 4, 3, 6) and (1, 4, 8, 2, 5) are not permitted.

3.4 Fitness function and the selection of parents

To select the parents in population to evolve for the next generation, we adopt the geometric function based on ranking order, that is, $\Pr ob(r) = q\ (1-p)^{r-1}$, $0<q<1$. where, r is a rank of fitness function and q is a parameter. Therefore, $\Pr ob(r)$ represents the probability of selection that has rank r in the fitness function. As q becomes larger, the difference of selection probability also becomes larger. If the number of population (Np) is a large number, the summation of probability becomes 1, approximately, that is, $\sum_{r=1}^{Np} \Pr ob(r) = \sum_{r=1}^{Np} q\ (1-p)^{r-1} \simeq\ 1$.

In the research of the genetic algorithm in FAP, to find a feasible solution rapidly, we count the number of infeasible constraints in constraints set (6) and (7), that is, we regard the number of infeasible constraints as a fitness function. To select the population in the previous population set, we assign a weight to the fitness value of each population.

3.5 Genetic operators

In this paper, we carried out two genetic operators, which are the crossover and mutation. The crossover operation is a phase that we generate the children objects from the parent. We adopted the order based crossover strategy that is developed by David[6]. To apply the strategy of David, we initially designate arbitrary two points in the string of gene. Offspring 1 is inherited the chromosomes between two cutting points from parent 1, and the remaining chromosomes are taken from parent 2 in the restriction of not taking the same chromosomes in the parent 1. Offspring 2 is inherited the genes as the same way except the sequence of choice for parents.

We give the crossover ratio as 25 %. In a crossover procedure, we generate a random number in the interval of [0, 99]. If the number is less than 25, we carry out the crossover process. Otherwise the crossover operation is not performed. Figure 5 is an example of crossover process.the parent 2. We start to bring the genes of latter part of offspring 1. The latter part of genes is (5 2). However the gene 5 already exists in the middle part of offspring 1. Therefore, we discard gene 5 and reselect the next candidate among the available set of gene. So, we accomplish the crossover process with O1=(1 8 9 | 4 5 6 7 | 2 3). The offspring 2 is got the same procedure of that of offspring 1.

Mutation is occurred in each generation as 5 % ratio. In a mutation procedure, we generate a random number in the interval of [0, 99]. If the number is less than 5, we carry out the mutation process. We take arbitrary two locations with random number generation in solution structure, and exchange the two genes. For example, we have the solution structure (1 8 9 4 5 6 7 2 3) and we obtain a number "4" from the random number generator, and it is less than 5 (this means it is included in the prescribed mutation ratio). And we select arbitrary two location 3 and 5, those are also decided by random number generator, we exchange the 3rd and 5th elements each other, finally we get another solution (1 8 *5* 4 *9* 6 7 2 3) after carrying out the mutation procedure.

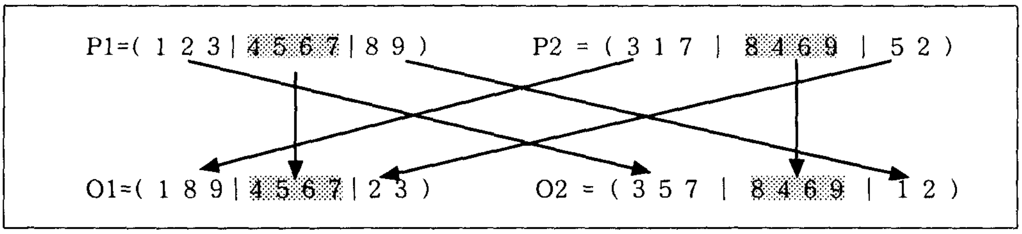


Figure 5. Crossover operation

3.6 Termination Criterion

We set the termination criterion the number of generation to be 100. Although we can have many types of criterion, the number of generation criterion is a simple and easy method.

4. Computational Results

With real data, the genetic algorithm of VHF system is tested. Since the operating policy of frequency is to use different frequency bands for the backbone and extension network, the VHF system can be decomposed into two independent networks. The backbone network is the primary network connected with SPIDER node systems and relay stations. On the other hand, extension network is the secondary network connected from units and/or terminals to the nodes or relay stations. The available three bands (Band I, II, III) have independent frequency intervals, that is, they have no intersection. The frequency intervals among bands are so wide to exclude co-site interference that we only consider the interference in a decomposed network. Band II is used for the backbone network and band I/III are applied for the extensions by the operating policy. Unfortunately, the available frequency band is not consecutive. They have separated and up-and-down features.

We solved FAP by 2-phase method. First, to exclude the far-site interference, we set the candidates of frequency by deciding the center frequency considering violation

Table 1. CPU second with Genetic Algorithm

Network / CPU Seconds	Backbone Network	Extension Network
Average*	20	14
Max	25	20
Min	14	10

* 2(3) tests could not find solution in backbone(extension) network. These cases are not counted.

of adjacent frequency scope. Each center frequency should be separated by the amount of interval for exclusion of far-site interference. The set of candidates can be shifted for generating different set of available frequency to the right or left direction. Second, we solve the FAP by genetic algorithm.

In a real data set, the available number of frequency was 33(23) and the number of edge was 16(12) for the backbone (extension) network on division size. The far-site interference separation is 5 MHz and co-site interference separations are 60/30/20 MHz (Band I/II/III), respectively. Co-site interference separations are clearly large amount compared with the available frequency band size.

We solved FAP for 50 times by the genetic algorithm. PC(Pentium 166MHz, 32 Mb memory) was used for the solution. Table 1 shows CPU seconds for solving FAP with genetic approach.

As Table 1 shows, genetic algorithm could solve FAP within 25 seconds. Among the 50 tests, genetic algorithm could not find solutions in 2 and 3 test problems of backbone and extension networks. However, in the almost all test problems, it provides solutions in a very short time. As the size of network grows, it is expected to take more time to get a feasible solution when we solve it by an IP approach. So, genetic algorithm approach is a successful method to find a solution.

5. Concluding Remarks

Frequency assignment problem is a critical issue on constructing infrastructure of communication system for next generation. Even though TD system has a lot of merits, it is difficult to allocate frequencies on the network since we should consider the co-site and far-site interference. When we change network configuration, we have to reallocate frequencies considering the interference on the side of overall view. In this paper, we formulate the FAP with Integer Programming model. Since FAP is an NP-hard problem, we approach to it by the genetic algorithm to obtain a feasible solution within a reasonable time. We made the initial population with random number generation, took order based selection strategies, operated crossover and mutation strategies.

As computational results show, the genetic algorithm approach solved the real problem successfully in a very short time. As the size of network grows, it is expected to take more time to get a feasible solution when we solve it by an IP approach. So, genetic algorithm approach is a successful method to find a solution. When we need to change network configuration slightly, we have to develop another method to change the violated frequency with one of the reserve frequency set. This paper handles only division-sized network configuration. When we need to reuse frequencies in corps-size, we can develop another method with FAP as sub-problem.

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