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MODIFIED SWEEP ALGORITHM FOR ROUTE SELECTION IN PUBLIC BUS ROUTING PROBLEM USING FUZZY DATA

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ABSTRACT

This paper investigates public bus route selection where demand is uncertain and evaluates the role of fuzzy logic in the MSA. The uncertain demand data are presented in linguistic form and transformed into fuzzy numbers. The crisp values obtained by the fuzzy logic are used to replace the exact demand in selecting best routes. The patterns of fuzzy data are presented to show capability of fuzzy data in representing exact data.

Keywords :

INTRODUCTION

The previous study on Modified Sweep Algorithm (MSA) proposes a solution to public bus routing problem in selecting best route based on demand. In this study, demand is known and the selection process is performed using exact data. In this paper, we investigate the route selection where demand is uncertain and evaluate the role of fuzzy logic in the MSA.

LITERATURE REVIEW

1. Public Bus Routes

The modified sweep algorithm is applied to public bus routes of a transportation company located in Semarang, Indonesia. Routes currently maintained by the company consist of 17 nodes and are connected by two-directed links as shown in Figure 1 (bold line). It is shown in Table 1 that there are two of four existing routes use the same links. The overlapped-links may cause a longer length of routes to be maintained by the company compared to non-overlapped-links. There is a centre point which connects all routes in the network. It is the policy of the company to take a node to be a central point in which buses from all directions pass through this node. This policy is important for passengers who need to change bus which leads to a different direction. These passengers do not have to follow the bus to the bus station to take another bus because this will take time. All bus stations in Semarang and in most cities in Indonesia are located near the city border. Therefore, by occurrence of the central point, passengers can shorten the trip to reach their destination. To implement the modified sweep algorithm, we add more nodes in the network as seen as thin lines in Figure 1. Each link carries a weight representing average number of demand which is concerned in route selection process. Most of both current and alternative links are two-directed. Several links are one-directed, i.e. links connecting nodes 4, 19, 21, to 7 and links connecting nodes 9 to 13, and 23 to 14.

Table 1: Original Links

Route	Link	Length (Km)
I	8-7-6-0-5-4-3-1-3-4-5-0-6-7-8	41
II	2-3-4-5-0-9-23-24-25-10-11-10-25-24-23-9-0-5-4-3-2	39
III	8-7-6-0-12-13-14-15-26-16-26-15-14-13-12-0-6-7-8	40
IV	6-0-12-13-14-15-26-16-17-16-26-15-14-13-12-0-6	36
Total		156

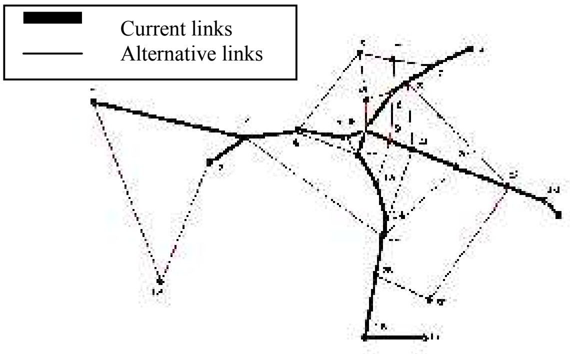


Figure 1: Current and Alternative Links

2. Modified Sweep Algorithm (MSA)

Modification is made to the second stage of the original sweep algorithm, i.e. Route Generation. In the first stage, clustering process is performed using the same procedure as used in the original sweep algorithm. A node is joined with its nearest neighbour based on its polar coordinate angle and the capacity of each vehicle. The objective of clustering in the modified sweep algorithm is to provide a procedure which enables user to easily group the available nodes and determine which cluster a node or link should be attached to. *Node[0]* is assumed to be the centre polar coordinate.

Since *node[0]* of the real data is located in coordinate *x=324* and *y=124*, we reformulate the calculation of polar coordinate angles. If the location of *node[0]* is denoted by x_0,y_0 then the location of *node[i]* is defined as x_i-x_0,y_i-y_0. The polar coordinate angle is defined using *sinus* function to suit the functions provided by Pascal programming language that is used in the experiment:

$$Sin\ \alpha_i=(y_i-y_0)/radian$$

where radian is defined by:

$$radian=\sqrt{((x_i-x_0)^2+(y_i-y_0)^2)}$$

After clustering process is completed, we have to analyze the list of links in each cluster. As mentioned previously, clustering process enables us to group the links and perform the route selection. The result may not satisfy the user because of reasons such as: the links attached in a cluster generate a very short route, or there are too many clusters. In the case of unsatisfactory clusters, we can make changes by replacing or deleting links in a cluster, and combining two clusters. When all clusters are set, we have to determine the start and end node in each cluster. In this case, start and end node are the nodes where the bus stations are located.

In the second stage, a thorough modification is made by replacing travelling salesman (TSP) route selection method with a weighted-directed search (WIDI). Unlike TSP which selects routes by combining nodes based on short distance, WIDI selects routes by combining links based on demand as explained in Section 5. Comparisons between SA and MSA are presented in Section 7.

In selecting a link to be attached to the generated route, there are several constraints that are considered. Assuming that *l[i,j]* is a link connecting node *i* to node *j* and *L* is a set of links from start node *node[1]* to end node *node[n]*, link $l[i,j] \in L$ if:

a. *weight[i,j]>=weight[i,j+1]*

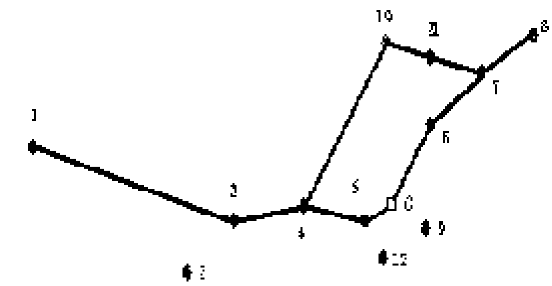
where: 0≤i≤MaxNode

0≤j≤MaxNode

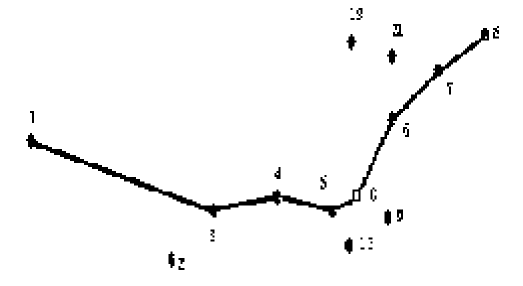
b. *node[i]* and *node[j]* are predecessors of *node[n]*

c. *i≠node[n]* and *j≠node[n-1]*

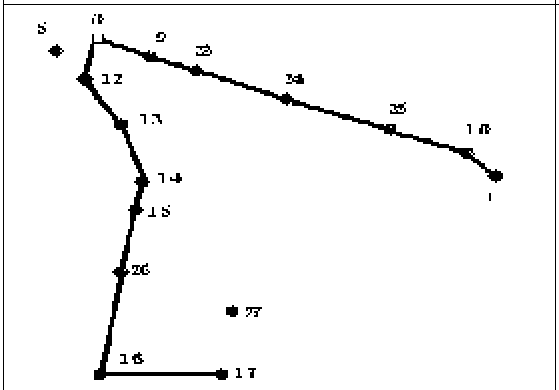
Figure 2 shows the result of the MSA for both forward and backward sweeps.



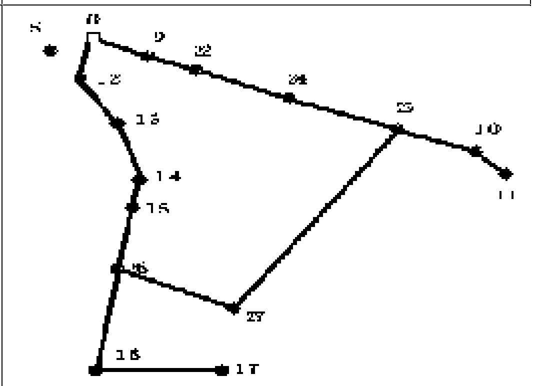
(a). Route I-A (Forward and Backward Sweep)



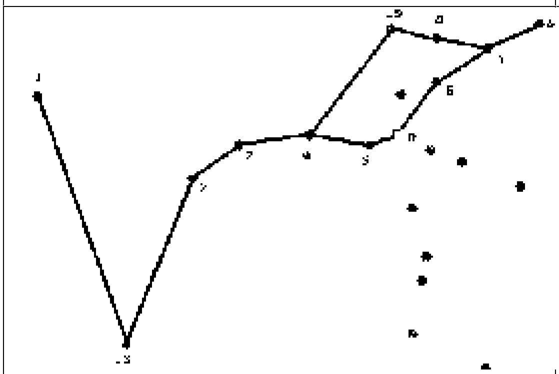
(b). Routes I-B, I-C, I-D (Forward Sweep) and I-C (Backward Sweep)



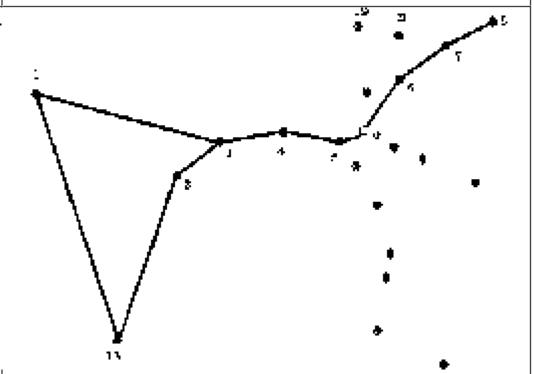
(c). Routes II-A, II-C (Forward Sweep) and II-C, II-D (Backward Sweep)



(d). Routes II-B, II-D (Forward Sweep) and II-A, II-B (Backward Sweep)



(e). Route I-B (Backward Sweep)



(f). Route I-D (Backward Sweep)

Figure 2 Results of Modified Sweep Algorithm in Graph

3. Fuzzy Demand Data

The MSA previously presented covers route selection when demand is certain. In this section, we present a solution to public bus routing problem when demand is uncertain. This problem occurs when the transport company is requested to serve more locations and new routes are required. In developing new routes where demand data are uncertain, the company estimates the number of demand by identifying public service places such as schools, hospitals, markets, offices, etc. In this paper, we propose a solution to route selection for public transport that is capable to use uncertain data.

4.1. Fuzzified Demand

Fuzzy logic is believed to be capable for capturing data ambiguity. The data can be represented as linguistic forms which indicate the levels of uncertainty of certain data. We assign a set of linguistic data representing demand at node D_i i.e. Very Low (VL), Low (L), Medium (M), High (H), and Very High (VH). Each data is represented by triangular fuzzy number $D_i=(d_1,dn_2,d_3)$ as seen Figure 3. The decision maker of the company can estimate that demand at the node will not less than d_1 or greater than d_3 based on his experience and intuition. Figure 4 shows the fuzzy sets of linguistic data for demand.

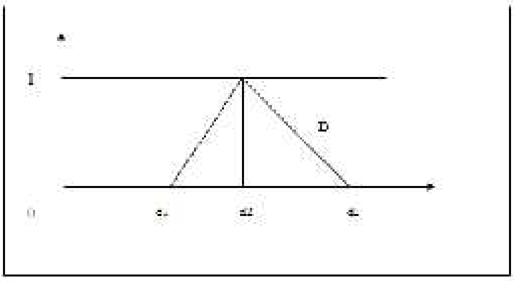


Figure 3 Triangular Fuzzy Number *D* Representing Demand

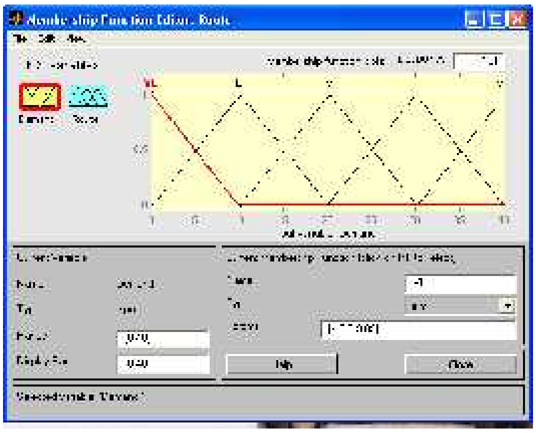


Figure 4 Demand Membership Functions

It is found that the demand membership functions have a disadvantage. Normally, a membership function represents a range number of demand. For example, membership function Medium may represent a range of demand from 10 to 20. Let us assume that we have to select one of two links A or B having number of demand 13 and 17 respectively. By using the exact data, we can easily select link B. In contrast, we cannot differentiate link A and B by using the membership function because both links have the same membership.

In order to solve this problem, we initiate an addition input, i.e. Preference that enables us to easily determine a degree of membership function. Preference represents the strength of user's preference in estimating demand data as a membership function. Preference is also presented as a triangular membership function including three degree of preferences i.e. Small, Fair, and Large. Therefore, the problem of selecting link A or B previously mentioned can be avoided. We can put a lower preference into the membership function of link A and, consequently, link B that has a higher preference is selected. Figure 5 shows the membership functions of Preference.

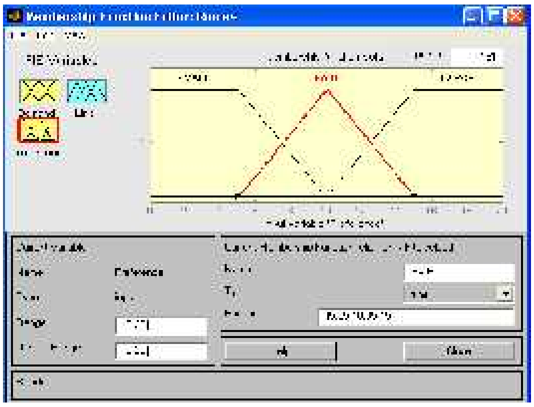


Figure 5 Preference Membership Functions

4.2.Rules and Defuzzification

Rules associate the fuzzy input to the output which is initialized before inferring the rules. We initiate five membership functions as the output consisting of Negative Large (NL), Negative Small (NS), Zero (ZE), Positive Small (PS), and Positive Large (PL) as seen in Figure 6. The output represents five membership functions of link which replaces the exact demand data used in the route selection process. We use centroid method for defuzzifying the input into a crisp value. The centroid method is formulated as:

$$F^{-1}(\tilde{A}) := \frac{\int_x \mu \tilde{A}(x) \,.\, x\, dx}{\int_x \mu \tilde{A}(x)\, dx}$$

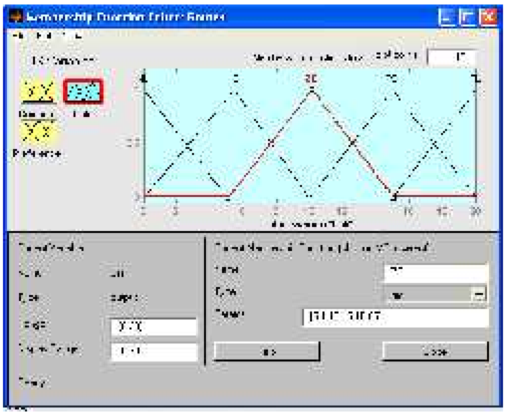


Figure 6 Link Membership Functions

The fuzzy inference engine employs a particular kind of fuzzy logic. It stimulates fuzzy knowledge base and fuzzy input to generate fuzzy decisions (Singh and Bailey, 1997). Arabshashi et al. (1997) defined the inference engine as the system decision maker and determines how the machine interprets the fuzzy linguistics. In a fuzzy inference, fuzzy logic principles are used to combine the fuzzy IF-THEN rules in the fuzzy rule base into a mapping from fuzzy sets in $U = U_1 \, x \, ... \, x \, U_n$ to fuzzy sets in V (Wang, 1994). Inference process is a decision making logic which determines fuzzy outputs corresponding to fuzzified inputs, with respect to fuzzy inference rules (Cai and Kwan, 1998).

A rule is fired when its consequent actions are executed. The inference engine will determine rule fireability, select rules for firing and execute the consequent actions. An inference procedure is required to determine the degree to which a rule is fired. The degree, to which rule fires, determines the contribution of its output fuzzy set (Parsons et al., 1995). In graphical representation, the firing of each fuzzy rule will contribute an area to the defuzzification procedure (Pang et al., 1995). Figure 7 shows the fuzzy associative matrix consisting of inference rules used to associate the fuzzified input with the defuzzified output.

	LOW	FAIR	LARGE
VL	NL	NL	NL
L	NL	NS	NS
M	NS	ZE	ZE
H	ZE	PS	PS
VH	PS	PL	PL

Figure 7 Fuzzy Associative Matrix

Figure 8 illustrates the fuzzy procedure involving Demand and Preference as the input and Link as the output. Notice that each graph has a range number from 0 to 20. The range number does not represent the number of demand but it only represents the location of input data given by the user. Data which is represented as graph are given by locating the vertical line provided in the graph. We can move the vertical line left or right and put it in the appropriate location as shown in the *input bar* as a pair of numbers consisting the location of demand and preference data. In Figure 8, the pair of input data [12.02 7] shows the location of demand data in the membership function is at 12.02 and the location of preference is 7. Note that *Demand=12* does not exactly represent the number of demand. The crisp value of this demand is 9.46 as shown is the membership function of Link. This result is used by the MSA in the route selection process. Figure 9 shows the surface of these membership functions.

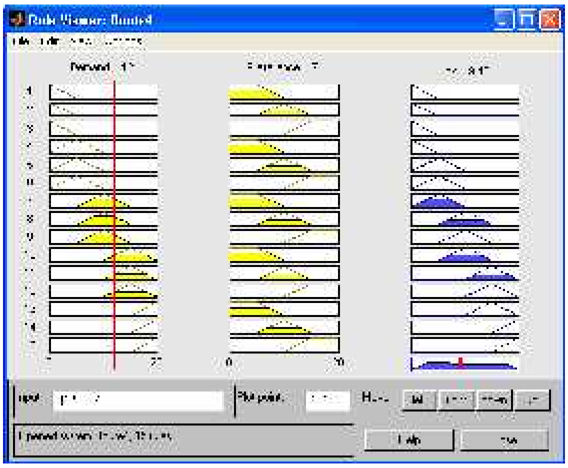


Figure 8 Fuzzy Result

4. Experimental Result

This experiment aims to find possibility of using fuzzy data when demand is unknown. As previously mentioned, the identification of fuzzy demand depends on the user's experience and intuition. Therefore, there are several possibilities of fuzzy sets identified by the user. In this section, we present the results based on two different sets of fuzzy data for both current and alternative links as shown in Table 2 and Table 3. Figure 10 and Figure 11 present the patterns of fuzzy demand compared to the exact demand. It is shown that the fuzzy data have similar patterns to the exact data.

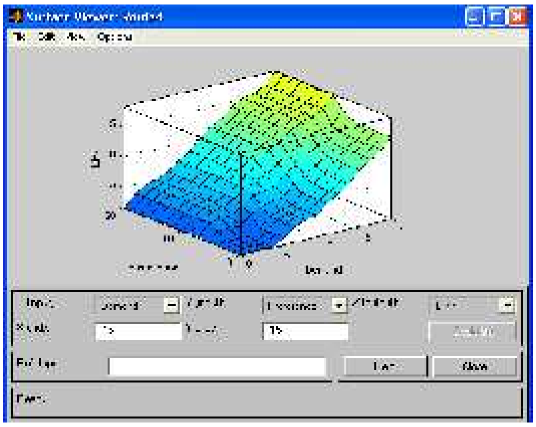


Figure 9 Data Surface

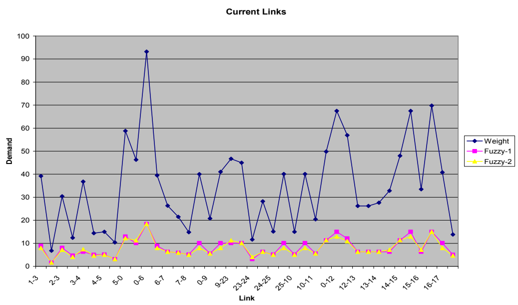


Figure 10 Demand Patterns on Current Links

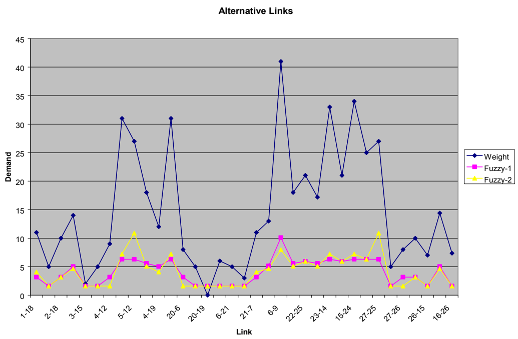


Figure 11 Demand Patterns on Alternative Links

5. Conclusion

Fuzzy data sets have similar pattern to the exact demand data and, therefore, they may be used to replace the exact data in the MSA to perform route selection. The fuzzy demand data identification is fully dependent on the user's experience and intuition. However, it is fairly certain that fuzzy logic is not necessarily used in the route selection when demand is the only concern. The fact that fuzzy demand data can be used in the MSA will be concerned in future study to put more variables in the route selection process.

Table 2: Current Links

Origin	Destination	Weight	Location 1	Fuzzy 1	Location 2	Fuzzy 2
1	3	39.2	[10 9]	8.91	[8 17]	7.98
3	1	6.8	[5 5]	1.6	[0 10]	1.66
2	3	30.4	[10 8]	8	[7 10]	7.22
3	2	12.4	[5 8]	4.65	[5 7]	4.07
3	4	36.8	[10 6]	6.3	[8 8]	7.46
4	3	14.4	[5 9]	5.01	[5 8]	4.65
4	5	15	[5 10]	5.14	[5 9]	5.01
5	4	10.4	[5 6]	3.15	[5 6]	3.15
5	0	58.8	[15 8]	12.9	[12 10]	12.2
0	5	46.3	[10 16]	10.1	[11 10]	11.3
0	6	93.2	[20 20]	18.4	[20 20]	18.4
6	0	39.5	[10 9]	8.91	[8 17]	7.98
6	7	26.3	[6 14]	6.29	[6 18]	6.29
7	6	21.5	[6 8]	5.92	[6 8]	5.92
7	8	14.8	[5 10]	5.14	[5 9]	5.01
8	7	40	[10 10]	10.1	[8 18]	7.98
0	9	20.8	[6 7]	5.57	[6 7]	5.57
9	0	41	[10 12]	10.1	[8 19]	7.98
9	23	46.7	[10 16]	10.1	[11 10]	11.3
23	9	45	[10 15]	10.1	[11 9]	10.1
23	24	11.6	[5 6]	3.15	[5 7]	4.07
24	23	28.2	[6 16]	6.29	[6 20]	6.29
24	25	15.1	[5 10]	5.14	[5 9]	5.01
25	24	40.1	[10 10]	10.1	[8 18]	7.98
25	10	15	[5 10]	5.14	[5 9]	5.01
10	25	40.1	[10 10]	10.1	[8 18]	7.98
10	11	20.4	[6 7]	5.57	[6 7]	5.57
11	10	49.8	[11 15]	11.3	[11 13]	11.4
0	12	67.5	[15 17]	15	[15 8]	12.9
12	0	56.9	[15 7]	12.1	[12 9]	10.9
12	13	26.2	[6 14]	6.29	[6 18]	6.29
13	12	26.2	[6 14]	6.29	[6 18]	6.29
13	14	27.6	[6 15]	6.29	[6 19]	6.29
14	13	32.8	[10 6]	6.3	[7 10]	7.22
14	15	48	[11 15]	11.3	[11 13]	11.4
15	14	67.5	[15 17]	15	[15 8]	12.9
15	16	33.5	[10 6]	6.3	[7 10]	7.22
16	15	69.8	[15 19]	15	[15 10]	15

16	17	40.8	[10 11]	10.1	[8 19]	7.98
17	16	13.8	[5 9]	5.01	[5 8]	4.65

Table 3: Alternative Links

Origin	Destination	Weight	Location 1	Fuzzy 1	Location 2	Fuzzy 2
1	18	11	[5 6]	3.15	[5 7]	4.07
18	1	5	[5 4]	1.6	[0 5]	1.6
2	18	10	[5 6]	3.15	[5 6]	3.15
18	2	14	[5 9]	5.01	[5 8]	4.65
3	15	2	[0 2]	1.6	[0 0]	1.6
15	3	5	[5 4]	1.6	[0 5]	1.6
4	12	9	[5 6]	3.15	[5 5]	1.6
12	4	31	[10 6]	6.3	[7 10]	7.22
5	12	27	[6 15]	6.29	[6 19]	10.9
12	5	18	[6 7]	5.57	[6 6]	5.08
4	19	12	[5 9]	5.01	[5 7]	4.07
0	20	31	[10 6]	6.3	[7 10]	7.22
20	6	8	[5 6]	3.15	[5 5]	1.6
19	20	5	[5 4]	1.6	[0 5]	1.6
20	19	0	[0 0]	1.6	[0 0]	1.6
19	21	6	[5 4]	1.6	[0 5]	1.6
6	21	5	[5 4]	1.6	[0 5]	1.6
21	6	3	[0 3]	1.6	[0 0]	1.6
21	7	11	[5 6]	3.15	[5 7]	4.07
7	22	13	[5 10]	5.14	[5 8]	4.65
6	9	41	[10 12]	10.1	[8 19]	7.98
22	23	18	[6 7]	5.57	[6 6]	5.08
22	25	21	[6 8]	5.92	[6 7]	5.92
9	13	17.2	[6 7]	5.57	[6 6]	5.08
23	14	33	[10 6]	6.3	[7 10]	7.22
24	15	21	[6 8]	5.92	[6 7]	5.92
15	24	34	[10 6]	6.3	[7 10]	7.22
25	27	25	[6 14]	6.29	[6 15]	6.29
27	25	27	[6 15]	6.29	[6 19]	10.9
26	27	5	[5 4]	1.6	[0 5]	1.6
27	26	8	[5 6]	3.15	[5 5]	1.6
15	26	10	[5 6]	3.15	[5 6]	3.15
26	15	7	[5 5]	1.6	[0 5]	1.6
26	16	14.4	[5 9]	5.01	[5 8]	4.65
16	26	7.36	[5 5]	1.6	[5 5]	1.6