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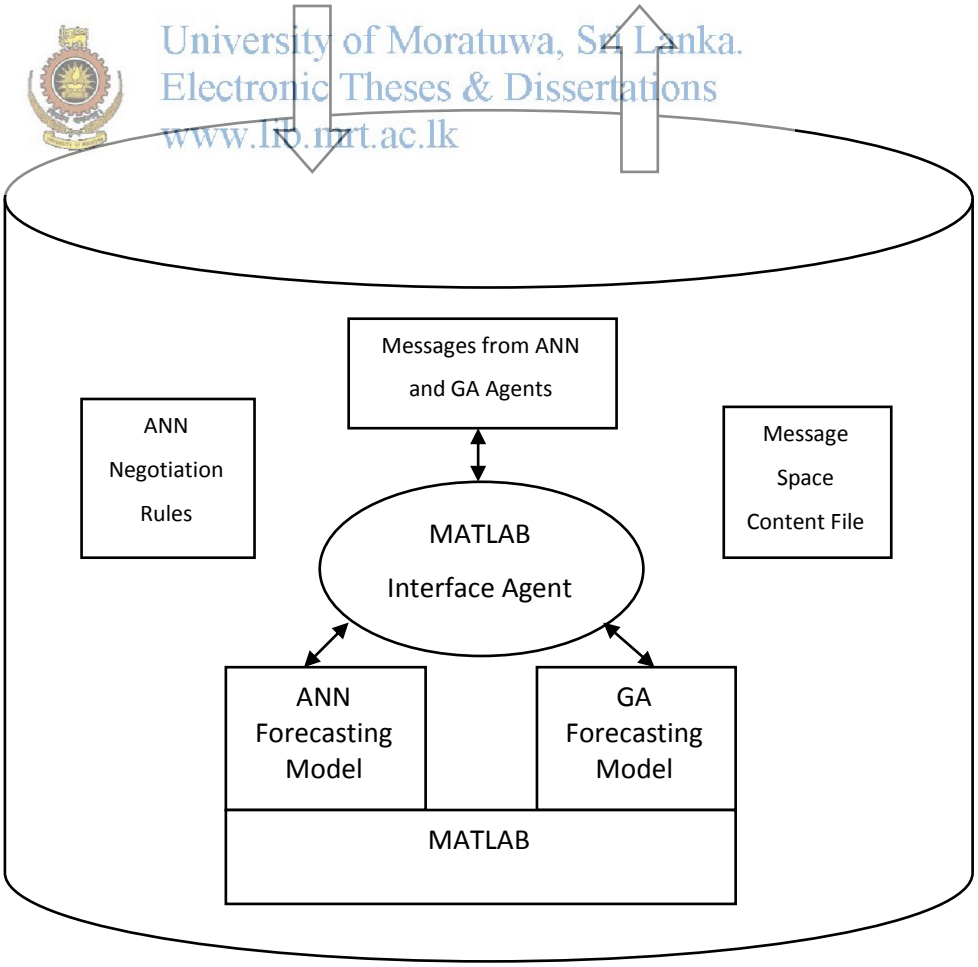
Appendix A:

The Block Diagram of the Ontology

A.1 Introduction

Following block diagram shows the more detailed view about ontology available in the system. It has two separate forecasting models based on the ANN and GA perspectives. Those models have designed and implemented on top of the MATLAB toolkit. Other modules are the ANN based negotiation rule base and the message space content file. The ANN rules have designed based on the theoretical and heuristic understanding on ANN technology. The message space content file is a XML file which manages the up-to-date information about all the agents in the system. The MATLAB interface agent efficiently manages the forecasting models (objects) resulted in the MATLAB framework and enable communication between those objects and the agents in the MAS.



Appendix B:

The Training Dataset

B.1 Introduction

The data set for training the forecasting models was taken from the meteorological department of Sri Lanka. This data set contains data on temperature, relative humidity and daily rainfall from 1st of Oct 2011 to 19th of Oct 2011 in Colombo city.

October-2011					
Date	Temperature (°C)		Relative Humidity (%)		Rainfall (mm)
	Max	Min	Day	Night	
1	31.2	26.6	71	82	0.0
2	31.3	25.3	73	84	1.2
3	31.4	26.0	73	80	0.1
4	31.3	26.6	73	81	0.0
5	31.6	27.6	72	79	0.0
6	31.4	26.2	69	80	0.0
7	31.5	25.4	68	77	0.1
8	31.2	26.0	67	82	1.0
9	31.6	26.0	72	78	0.1
10	31.3	27.8	70	78	0.1
11	31.6	26.0	67	85	2.3
12	30.8	25.9	82	88	2.8
13	31.5	24.9	76	87	0.2
14	31.0	26.4	78	95	3.2
15	31.5	25.1	76	85	0.0
16	31.7	25.2	71	86	59.1
17	31.0	23.5	75	87	2.8
18	31.1	24.7	72	90	26.2
19	31.2	24.6	73	93	5.7
20	30.2	24.8	77	94	1.2

October-2011					
Date	Temperature (^{o}C)		Relative Humidity (%)		Rainfall (mm)
	Max	Min	Day	Night	
21	30.7	24.5	76	95	38.9
22	30.2	24.8	79	93	0.1
23	30.6	24.5	80	96	17.4
24	30.2	23.6	82	96	34.2
25	30.3	24.0	83	95	6.7
26	30.4	24.2	74	92	0.1
27	30.4	24.6	79	96	6.2
28	32.5	24.0	72	94	5.5
29	29.8	24.2	81	96	13.3
30	30.3	24.1	82	95	7.2
31	30.1	24.4	78	94	6.8

November-2011					
Date	Temperature (oC)		Relative Humidity (%)		Rainfall (mm)
	Max	Min	Day	Night	
1	28.2	24.6	91	96	47.7
2	29.3	23.7	83	96	37.6
3	29.5	23.7	83	93	4.9
4	30.7	24.2	75	92	0.1
5	30.6	25.2	77	92	0.0
6	31.1	25.2	76	94	2.5
7	31.1	24.3	74	96	7.7
8	31.3	23.1	68	88	0.0
9	31.9	23.6	63	74	0.0
10	31.7	23.9	53	84	0.0

November-2011					
Date	Temperature (oC)		Relative Humidity (%)		Rainfall (mm)
	Max	Min	Day	Night	
11	32.4	24.0	56	87	0.0
12	31.9	24.6	66	89	0.0
13	31.9	24.4	71	93	1.4
14	30.8	24.2	75	85	0.0
15	32.6	24.1	66	88	0.0
16	31.8	24.8	68	86	0.0
17	31.7	24.8	69	91	0.1
18	31.6	25.4	70	92	0.9
19	31.5	24.4	74	95	14.1

Appendix C:

The Test Dataset

C.1 Introduction

The training dataset has taken from the collected weather data at Colombo city from 19th of November 2011 to 30th of November 2011.

November-2011					
Date	Temperature (oC)		Relative Humidity (%)		Rainfall (mm)
	Max	Min	Day	Night	
19	31.5	24.4	74	95	14.1
20	30.3	25.0	79	89	0.7
21	30.6	24.4	80	92	15.3
22	31.6	23.8	65	87	4.5
23	30.7	24.2	74	89	0.0
24	30.6	24.8	81	94	1.7
25	26.6	24.6	89	92	17.9
26	30.9	23.1	73	87	6.0
27	31.3	24.4	75	92	4.5
28	29.2	23.7	75	94	0.1
29	30.6	24.7	74	90	0.0
30	30.3	25.2	84	97	26.3

Appendix D:

Results

D.1 Introduction

The testing dataset used to generate forecast from the MAS model. For the input weather conditions those are belong to a particular day and the relevant resulted forecasts from the negotiations have tabulated in rest of the section. The negotiation attempts were controlled into set of attempts such as five attempts, ten attempts and twenty attempts. All the results and their summaries are available as follows.

D.2 Results of Five Negotiation Attempts

Results of Five Negotiation Attempts								
Date	20			21			22	
Agent	ANN	GA		ANN	GA		ANN	GA
Results	4.3	0.3		12.4	0.3		9.4	6.3
	15.7	13		12.1	1.1		10.9	9.8
	13.2	12.4		13.1	9.3		10.2	3.2
	9	5.8		15.4	16.9		10.3	12.4
	12.9	13.5		25.4	3		16.2	5.8
Date	23			24			25	
Agent	ANN	GA		ANN	GA		ANN	GA
Results	3.7	2.1		6.6	10.5		12.5	1.2
	3.4	4.3		10	4.7		15.6	0.3
	1.4	0.3		10.4	0.5		12.3	5.6
	2.3	0.2		9.7	12.8		11.1	5.4
	4.5	4.3		11.5	0.2		11.9	9.9
Date	26			27			28	
Agent	ANN	GA		ANN	GA		ANN	GA
Results	46.5	18.6		3.2	0.5		4.6	2.3
	13.1	4.2		8.3	5.4		9.8	2.3

Results of Five Negotiation Attempts								
	14.7	5.4		1.7	0.5		6.9	0.8
	5	5.1		9.2	0.2		7.6	1.7
	26.8	13.8		7.9	0.8		7.5	8.4
Date	29			30				
Agent	ANN	GA		ANN	GA			
Results	30.1	0.2		8.5	5			
Results	10.7	8		8.9	10.8			
	10.5	2.9		6.7	11.7			
	8.8	0.2		4.9	6.8			
	7.3	6		8.6	5.3			

D.3 Summarized Results of Five Negotiation Attempts

Date	ANN	GA	Actual
20-Nov	12.9	13.5	0.7
21-Nov	15.4	16.9	15.3
22-Nov	10.9	9.8	4.5
23-Nov	4.5	4.3	0
24-Nov	9.7	12.8	1.7
25-Nov	11.9	9.9	17.9
26-Nov	5	5.1	6
27-Nov	1.7	0.5	4.5
28-Nov	7.5	8.4	0.1
29-Nov	7.3	6	0
30-Nov	4.9	6.8	26.3

D.4 Results of Ten Negotiation Attempts

Results of Ten Negotiation Attempts								
Date	20			21			22	
Agent	ANN	GA		ANN	GA		ANN	GA
Results	4.3	0.3		12.4	10		9.4	0.3
	15.7	13		12.5	11.4		9.6	1.3
	13.2	12.4		14.9	1		14.9	13.3
	9	5.8		19.1	11.3		15.2	25.7
	12.9	13.5		18.8	22.5		12.5	9.3
	8.3	8.2		14.9	0.8		11	0.4
	13.8	6.8		17.1	14.8		17.3	7.5
	16.9	4.8		14.9	11.7		12.3	9.4
	11.6	0.7		14.6	11		14	5.5
	22.5	4.6		10.3	16.8		10.4	6.4
Date	23			24			25	
Agent	ANN	GA		ANN	GA		ANN	GA
Results	3.7	7.2		6.6	8		12.5	8.4
	3.3	3.9		9.8	5.9		9.9	4.4
	4.7	6.6		9.3	0.2		10.7	3
	3.2	3.6		11.9	3.6		17.3	17.8
	6	0.6		10.4	4.5		10.2	12.8
	-0.8	0		7.4	4		14.2	3.1
	8.3	2.5		7.4	1.5		12.4	18.1
	3.3	2.2		6	3		14.5	19.2
	5.9	0.3		7.3	10		11.7	13.9
	5.9	2.7		11.6	7.4		8.2	11.3
Date	26			27			28	
Agent	ANN	GA		ANN	GA		ANN	GA

Results of Ten Negotiation Attempts								
Results	46.5	5		3.2	0.8		4.6	5.6
	31.8	13.7		9.5	8.9		8.3	8.7
	20.3	8.5		6.3	2.3		6.4	0.4
	12.9	20.4		5.6	10.8		7.8	7.1
	14.3	11.4		9.9	2		8.9	6.2
	14	0.4		6.4	5.8		8.1	1.1
	38.9	0.4		7.7	0.7		7.8	2.9
	14.7	2.3		9.5	6.3		2.9	2.7
	35.1	5.1		5.5	0.5		4.9	0.4
	23.5	22.2		8.4	0.3		7.4	1.6
Date	29			30				
Agent	ANN	GA		ANN	GA			
Results	30.1	4.2		8.5	8.8			
	14	5.1		7.8	6.7			
	12.8	8.5		9.2	0.1			
	13.1	9.2		6.8	10.3			
	7.3	1		8.4	8.1			
	12.3	4.1		7.9	3.2			
	13.1	13.8		6.1	2.3			
	12.5	7.1		8.3	0.5			
	12.9	6.2		6.8	1.2			
	4	4		10.9	0.5			

D.5 Summarized Results of Ten Negotiation Attempts

Date	ANN	GA	Actual
20-Nov	8.3	8.2	0.7
21-Nov	12.5	11.4	15.3
22-Nov	14.9	13.3	4.5
23-Nov	3.2	3.6	0
24-Nov	6.6	8	1.7
25-Nov	17.3	17.8	17.9
26-Nov	23.5	22.2	6
27-Nov	9.5	8.9	4.5
28-Nov	2.9	2.7	0.1
29-Nov	4	4	0
30-Nov	8.5	8.8	26.3

D.6 Results of Twenty Negotiation Attempts

Results of Twenty Negotiation Attempts								
Date	20			21			22	
Agent	ANN	GA		ANN	GA		ANN	GA
Results	4.3	0.3		12.4	6.9		9.4	6.6
	15.7	13		12.3	1.7		14.1	4.1
	13.2	12.4		11.6	8.5		10.8	15.1
	9	5.8		18.2	6.3		15.7	14.2
	12.9	13.5		15.7	2.2		9	5.6
	8.3	8.2		13.5	0.3		11.3	6.9
	13.8	6.8		16.1	19.9		12.9	7.1
	16.9	4.8		12.9	2.6		15.6	0.6
	11.6	0.7		16.7	4.6		20.1	0.2
	22.5	4.6		17.7	22.5		14	7.5
	16.2	9.8		15.9	7.8		16.5	3.9
	6.1	2		23.1	9		15	3.5
	8.5	0.8		25.3	6.9		16	7.9
	15.9	2.5		27.8	4.3		16	10.5
	15.2	4.8		19.7	24.6		11.6	5.9
	11.4	5.1		25.3	0.2		14.3	11
	13.2	9.4		17.1	7.1		10.7	0.4
	9.4	12.3		12.1	0.6		14.1	5.8
	13.5	0.7		18.6	5.2		13.9	10
	17.9	2.6		20.8	5.4		24.8	0.1
Date	23			24			25	
Agent	ANN	GA		ANN	GA		ANN	GA
Results	3.7	0.7		6.6	5.1		12.5	2.8
	1.8	3		8.5	1.6		18	4.5
	-4.2	0		8.9	2.8		17.9	27
	2.2	0.5		9.6	7.5		11.5	2.3

Results of Twenty Negotiation Attempts								
	5.8	1.2		8.8	6.6		17.3	7.2
	-1.2	0		10.2	9.1		11.8	0.2
	3.1	1.1		12	9.1		11.4	19.8
	4.9	2.3		9.7	3.8		11.7	8.8
	6	0.3		7	6.4		15	10.3
	6	0.7		10.6	10		12.5	0.3
	6.8	7.9		11.4	11.2		13.3	2.4
	3.6	4.2		7.9	12.4		12.4	1.3
	9.3	8.3		12.6	16.1		17.7	10.9
	1.7	0.9		11.4	0.9		11.4	11.6
	0.8	0.2		8.8	3.6		14.4	7.2
	2	2.2		12.5	1.4		16.8	2.4
	7.3	7.4		9	2.8		14.8	2.2
	-0.1	0		12.6	11.7		20.3	1.2
	9.5	15.8		10.6	0.5		12.4	11.4
	6.4	7.3		5.5	0.1		15.7	2.5
Date	26			27			28	
Agent	ANN	GA		ANN	GA		ANN	GA
Results	46.5	0.9		3.2	0.8		4.6	0.2
	21.8	0.5		5.2	0.9		5	0.1
	22.7	11.6		4.5	0.1		6.5	6
	13.7	9.9		2.6	2.1		7.6	2.3
	19.4	6.9		9	13.7		8.7	0.2
	28.1	1.3		5.3	9.1		8.6	4.5
	17.3	1		2.9	1.5		7.7	7.4
	29.6	9.3		6.6	7.5		7.5	0.4
	27.8	4.5		7.3	5.3		8.5	5.4
	27.8	4.4		6.2	0.7		6.7	5.4
	37.5	16.2		9.6	11.2		7.1	3
	38.1	7.3		6	5.5		7	4.1

Results of Twenty Negotiation Attempts								
	30	0.9		10.6	12.9		-2.9	0
	13	10.9		9.7	7.8		7.7	0.9
	24.8	2.7		4.6	7.9		9.8	3.4
	19.2	1.9		8.3	6		9.3	4.7
	36.2	16.4		6.8	4.5		10.2	6.3
	29	6		9.3	0.3		8.4	7.3
	11.9	7.7		12.1	5.3		6.5	10.1
	15.2	0.7		15.4	1.5		7.8	11.4
Date	29			30				
Agent	ANN	GA		ANN	GA			
Results	30.1	15.7		8.5	0.3			
	11.6	5.7		9.8	8			
	9.1	11.9		9.3	14.4			
	14.2	0.3		6.9	0.2			
	14.3	3.2		8	9.2			
	10.1	7.8		8.5	2.9			
	13.8	6.3		9	0.4			
	2.7	2.1		5.1	3.2			
	10.6	0.6		6.2	6.2			
	15.3	4.4						
	8.3	0						
	13.4	11.7						
	9.5	1.3						
	7.9	0.2						
	13.4	9.5						
	11.6	0.2						
	9.6	17.6						
	7.1	6.2						
	11.8	0.2						
	14.9	13.2						

D.7 Summarized Results of Twenty Negotiation Attempts

Date	ANN	GA	Actual
20-Nov	8.3	8.2	0.7
21-Nov	11.6	8.5	15.3
22-Nov	15.7	14.2	4.5
23-Nov	-0.1	0	0
24-Nov	11.4	11.2	1.7
25-Nov	11.4	11.6	17.9
26-Nov	13	10.9	6
27-Nov	2.6	2.1	4.5
28-Nov	7.7	7.4	0.1
29-Nov	2.7	2.1	0
30-Nov	6.2	6.2	26.3

Appendix E:

Fitness Function for the GA Model

*"A **fitness function** is a particular type of objective function that is used to summaries, as a single figure of merit, how close a given design solution is to achieving the set aims.*

In particular, in the fields of genetic programming and genetic algorithms, each design solution is represented as a string of numbers (referred to as a chromosome). After each round of testing, or simulation, the idea is to delete the 'n' worst design solutions, and to breed 'n' new ones from the best design solutions. Each design solution, therefore, needs to be awarded a figure of merit, to indicate how close it came to meeting the overall specification, and this is generated by applying the fitness function to the test, or simulation, results obtained from that solution.

The reason that genetic algorithms are not a lazy way of performing design work is precisely because of the effort involved in designing a workable fitness function. Even though it is no longer the human designer, but the computer, that comes up with the final design, it is the human designer who has to design the fitness function. If this is designed wrongly, the algorithm will either converge on an inappropriate solution, or will have difficulty converging at all.

Moreover, the fitness function must not only correlate closely with the designer's goal, it must also be computed quickly. Speed of execution is very important, as a typical genetic algorithm must be iterated many times in order to produce a usable result for a non-trivial problem.

Fitness approximation may be appropriate, especially in the following cases:

- *Fitness computation time of a single solution is extremely high*
- *Precise model for fitness computation is missing*
- *The fitness function is uncertain or noisy.*

Two main classes of fitness functions exist: one where the fitness function does not change, as in optimizing a fixed function or testing with a fixed set of test cases; and one where the fitness function is mutable, as in niche differentiation or co-evolving the set of test cases.

Another way of looking at fitness functions is in terms of a fitness landscape, which shows the fitness for each possible chromosome.

Definition of the fitness function is not straightforward in many cases and often is performed iteratively if the fittest solutions produced by GA are not what are desired. In some cases, it is very hard or impossible to come up even with a guess of what fitness function definition might be. Interactive genetic algorithms address this difficulty by outsourcing evaluation to external agents (normally humans). (Reference: http://en.wikipedia.org/wiki/Fitness_function)"

According to the co-evolving nature of the weather forecasting problem, designed the co-evolvable fitness function which evolves with the current weather conditions. The developed fitness function is available follows.

```
a = MaxT-MinT
b = RHN-RHD
function z = fitness_fun(x)
z = a*(x(1) +x(2)) +b*(x(3) + x(4)) + x(5)+x(6);
```

Here ‘a’ and ‘b’ are evolvable constants. They are based on present conditions such as Temperature range and the range of the Relative humidity. In order to minimize the fitness ‘z’ value ‘a’ and ‘b’ must be minimized. According to the heuristics knowledge about weather conditions’ differences of those variables will not change rapidly over the time. It is a gradual process. Therefore it can conclude the function ‘z’ as the fitness function.