Enhancing Path Selection in Multihomed Nodes

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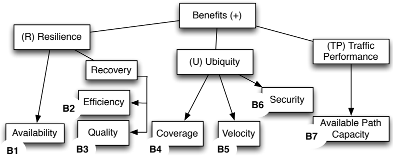
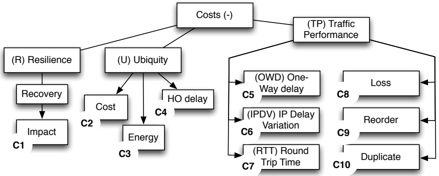
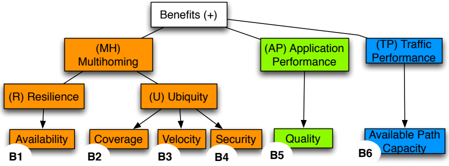
Outline

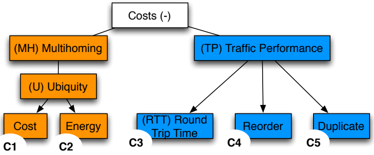
Introduction

Path selection in multi-interface nodes (multihomed), multiaccess capable can be a **NP-Hard** problem.









Related Work

Linear Programming (LP) techniques

- ✓ Support weighting of criteria;
- ✓ Optimal Solution;
- ✗ Require Adaptation.

Multiple Attribute Decision Mechanism (MADM) techniques

- ✓ Not tied to the problem being solved/optimized;
- ✓ Applied in distinct areas (e.g. social sciences, economical);
- ✓ Flexible to include diverse criteria;
- ✓ Support weighting of criteria.

MADM steps

- **Step 1 - Decision Matrix** For *nb* benefits and *nc* costs criteria.
- **Step 2 - Normalization** $r_{ij} = \frac{x_{ij}}{\sqrt{\sum x_{ij}^2}}$ $for\ i = 1, \cdots, m; j = 1, \cdots, n.$
- **Step 3 - Weighting** $v_{ij} = w_j \cdot r_{ij}$, with $\sum w_j = 1$
- **Step 4 - Ideal Solutions** Positive-ideal and negative-ideal solutions are determined by A^* and A^- terms, respectively:

$$A^* = \{v_1^*, v_2^*, \cdots, v_{nb}^*\}$$
$$A^- = \{v_1^-, v_2^-, \cdots, v_{nb}^-\}$$

Where: $$v_j^* = max(v_{i,j})\ \forall i = 1, \cdots, m\ j = 1, \cdots, nb$$
$$v_j^- = min(v_{i,j})\ \forall i = 1, \cdots, m\ j = 1, \cdots, nc$$

- **Step 5 - Distance**

Step	TOPSIS[a,c]	DiA[a,c]	MeTH[a,b,c,d]
Distance	$D_i = \sqrt{Id_j - v_{i,j}}$	$D_i = \lvert Id_j - v_{i,j} \rvert$	$D_i = \frac{(Id_j - v_{i,j})^2}{\lvert Id_j - Sd_j \rvert + \alpha}$
Score	$S_i = \frac{D_i^-}{D_i^- + D_i^*}$	$S_i = \sqrt{(D_i^*)^2 + (D_i^-)^2}$	$S_i = \sqrt{D_i^* + D_i^-}$
Rank	Best=descend(S_i)	Best=ascend(S_i)	Best=ascend(S_i)

[a] Id_j is the Ideal solution.
[b] Benefits: $Sd_j = \overline{X_j} + Var(X_j)$; Costs: $Sd_j = \overline{X_j} - Var(X_j)$
[c] Benefits: D_i^*; Costs: D_i^-
[d] $\alpha = 0.001$

- **Step 6 - Score**
- **Step 7 - Ranking**

These steps apply to MulTiHOming-aware Decision-makIng meChanism for AppLications (MeTHODICAL), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and Distance to Ideal Alternative (DiA) MADM techniques.

Evaluating and comparing MADM techniques

Common MADM evaluations:

- ✓ Use sub-representative evaluation metrics (e.g. normalization functions);
- ✓ Metrics are tied to a scenario (e.g. number of handovers);
- ✓ Do not promote comparison between MADM techniques.

What is the best MADM technique?

Methodology to evaluate MADM techniques

Based on standardized techniques:

- Design of Experiments (DoE);
- Analysis of Variance Variance (ANOVA)
  - Model interactions;
  - Significance $p - value < 0.05$;
  - Model completeness;
  - Coefficient of determination R^2 $\rightarrow$ Explains variance of Y (score);
  - F-statistic $\rightarrow$ variance between experiments;
- Factorial Design 2^k, n^k.

Id	x_1	x_2	x_3	**Effect**
1	-	-	-	(1)
2	+	-	-	x_1
3	-	+	-	x_2
4	+	+	-	x_1x_2
5	-	-	+	x_3
6	+	-	+	x_1x_3
7	-	+	+	x_2x_3
8	+	+	+	$x_1x_2x_3$

$$
\begin{aligned}
Y = & \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \\
& \beta_4 x_1 x_2 + \beta_5 x_1 x_3 + \\
& \beta_6 x_2 x_3 + \beta_7 x_1 x_2 x_3 + \epsilon
\end{aligned}
$$

Methodology to evaluate MADM techniques (cont'd)

Includes the following steps:

- **Step 1 - Decision Matrices** $dM_n[m, k]$, with m measurements for the n paths with k criteria;
- **Step 2 - Levels** $lMin$ corresponds to the minimum level (-) while $lMax$ corresponds to the maximum level $(+)$;

$$lMin_j = min(dM_1[,j], dM_2[,j], \cdots, dM_n[,j]) \; with \; j = 1, \cdots, k \rightarrow 2^k$$
$$lMax_j = max(dM_1[,j], dM_2[,j], \cdots, dM_n[,j]) \; with \; j = 1, \cdots, k \rightarrow 2^k$$
$$lMax_j = \left[max(dM_1[,j]), \cdots, max(dM_n[,j])\right] \; with \; j = 1, \cdots, k \; \rightarrow n^k$$

- **Step 3 - Experiments Matrix** $dW_{sets}[z, k]$ corresponds to matrix with weight sets for z experiments;
- **Step 4 - Factorial design matrix** $dF[a, k]$, with a relying on the factorial design, $a = 2^k$ or $a = n^k$;

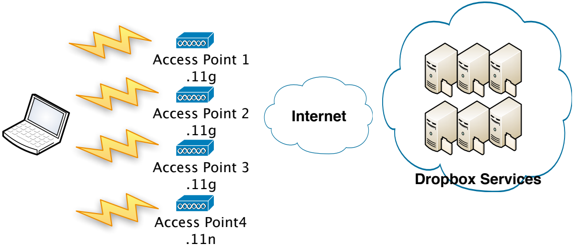
Methodology to evaluate MADM techniques (cont'd)

- **Step 5 - Input Matrix** Run MADM techniques has the full set of factors $dF[a,k]$ and weight sets $dW_{sets}[z,k]$ as input, forming the input matrix, $dI[a,k+z]$;

$$\text{dI[a, k + z]} = \begin{array}{c c} & \begin{array}{ccccccc} k_1 & \cdots & k_k & z1 & z2 & \cdots & z_z \end{array} \\ \begin{array}{c} 1 \\ 2 \\ \vdots \\ a \end{array} & \begin{bmatrix} level_{1,1} & \cdots & level_{1,k} & Score_{1,k+1} & Score_{1,k+2} & \cdots & Score_{1,k+z} \\ level_{2,1} & \cdots & level_{2,k} & Score_{2,k+1} & Score_{2,k+2} & \cdots & Score_{2,k+z} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots \\ level_{a,1} & \cdots & level_{a,k} & Score_{a,k+1} & Score_{a,k+2} & \cdots & Score_{a,k+z} \end{bmatrix} \end{array}$$

- **Step 6 - ANOVA** Response variable is Y (score);
- **Step 7 - Model** Validate model regarding ANOVA requirements, normality, homogeneity, independence and significance $p - value < 0.05$;
- **Step 8 - Analyse Model** Regarding completeness, F-statistic, and coefficient of determination R^2.

Dropbox

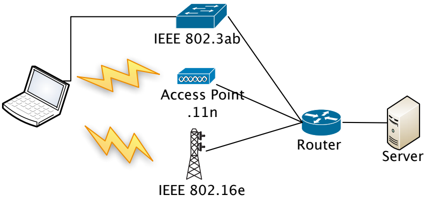


- Outside control (data collected by others);
- Can be reproduced as traces are available.

Paths	Benefits Criteria			Costs Criteria		
	(Sec)	(Cov)	(BW)	(Jitter)	(RTT)	(Loss)
P1	1; 7	0; 250	0; 300	0.20; 575.31	62.48; 171.79	0; 0.40
P2	1; 7	0; 100	0; 54	1.5; 999.1531	46.32; 166.27	0; 0.11
P3	1; 3	0; 100	0; 54	0.20; 10105.49	75.35; 5141.21	0; 0
P4	1; 5	0; 100	0; 54	0; 1126.61	0; 259.78	0; 0.18

Evaluation Scenarios (cont'd)

Heterogenous



- Under control;
- Metrics measured with One Way Active Measurement Protocol (OWAMP).

Paths	Benefits Criteria			Costs Criteria		
	(Sec)	(Cov)	(BW)	(Jitter)	(RTT)	(Loss)
P1	1; 7	0; 54000	0.8821144; 16.81217	0.0; 312.0	0.0; 202.7	0; 0.67
P2	1; 7	0; 250	32.27258; 56.85376	0.1; 6.4	1.1; 21.6	0; 0
P3	1; 7	0; 100	89.99288; 91.26333	0.0; 3.5	0.2; 21.2	0; 0

Evaluation Methodology

Weights sets and Input matrix $dI[a, k+z]$

Set	W_{Sec}	W_{Cov}	W_{BW}	W_{Jitter}	W_{RTT}	W_{Loss}
1	0.33	0.33	0.33	0.33	0.33	0.33
2	0.33	0.33	0.33	0.6	0.2	0.2
3	0.33	0.33	0.33	0.2	0.6	0.2
4	0.33	0.33	0.33	0.2	0.2	0.6
5	0.6	0.2	0.2	0.33	0.33	0.33
6	0.6	0.2	0.2	0.6	0.2	0.2
7	0.6	0.2	0.2	0.2	0.6	0.2
8	0.6	0.2	0.2	0.2	0.2	0.6
9	0.2	0.6	0.2	0.33	0.33	0.33
10	0.2	0.6	0.2	0.6	0.2	0.2
11	0.2	0.6	0.2	0.2	0.6	0.2
12	0.2	0.6	0.2	0.2	0.2	0.6
13	0.2	0.2	0.6	0.33	0.33	0.33
14	0.2	0.2	0.6	0.6	0.2	0.2
15	0.2	0.2	0.6	0.2	0.6	0.2
16	0.2	0.2	0.6	0.2	0.2	0.6

DropBox scenario
$dI_{Drop}[4^6, 6+16]$

Heterogeneous scenario
$dI_{Het}[3^6, 6+16]$

Results DropBox scenario

Statistical Models

$$Y_{ImMeth} = BW + RTT + Jitter + Loss + Cov + \text{BW:Cov}+ \\ \text{BW:RTT:Cov} + \text{BW:Jitter:Cov}+ \\ \text{BW:Loss:Cov} + \text{BW:RTT:Jitter:Cov}+ \\ \text{BW:RTT:Loss:Cov} + \text{BW:Jitter:Loss:Cov}$$

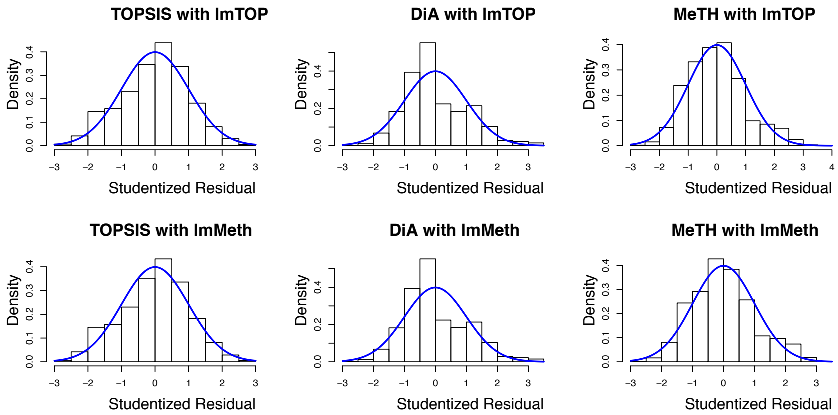
$$Y_{ImTOP} = BW + RTT + Jitter + Loss + Cov$$

ANOVA metrics

method	model	signif	interactions	R^2	F-statistic
TOPSIS	ImTOP	yes	no	0.5274	14624.2727
DiA	ImTOP	yes	no	0.4452	10518.2098
MeTH	ImTOP	yes	no	0.7240	34376.5185
TOPSIS	ImMeth	no	yes	0.5274	6093.3300
DiA	ImMeth	no	yes	0.4452	4382.2384
MeTH	ImMeth	yes	yes	0.7413	15649.5765

Results DropBox scenario (cont'd)

Normality



Results Heterogenous scenario

Statistical Models

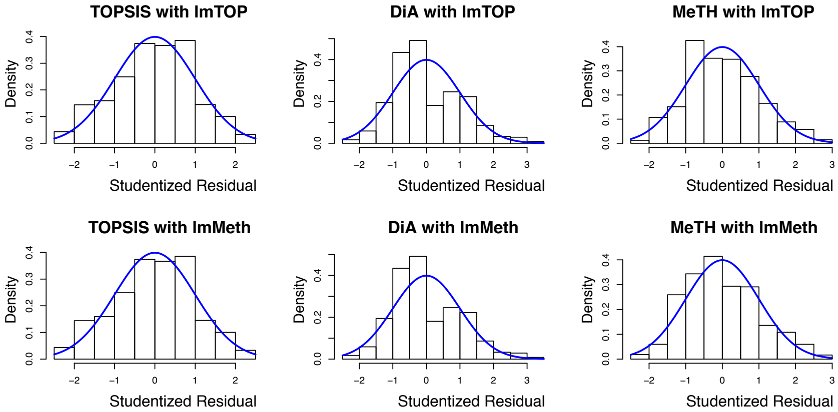
$$Y_{ImMeTH} = BW + RTT + Jitter + Loss + Cov + \mathrm{BW{:}Jitter} + \mathrm{BW{:}Loss} + \mathrm{BW{:}Cov} + \mathrm{BW{:}RTT{:}Cov} + \mathrm{BW{:}Jitter{:}Cov} + \mathrm{BW{:}Loss{:}Cov} + \mathrm{BW{:}RTT{:}Jitter{:}Cov} + \mathrm{BW{:}RTT{:}Loss{:}Cov} + \mathrm{BW{:}Jitter{:}Loss{:}Cov}$$

$$Y_{ImTOP} = BW + RTT + Jitter + Loss + Cov$$

ANOVA metrics

method	model	signif	interactions	R^2	F-statistic
TOPSIS	ImTOP	yes	no	0.5352	2684.5152
DiA	ImTOP	yes	no	0.4313	1768.3257
MeTH	ImTOP	yes	no	0.7514	7046.4885
TOPSIS	ImMeth	no	yes	0.5352	958.0181
DiA	ImMeth	no	yes	0.4313	631.0595
MeTH	ImMeth	yes	yes	0.7963	3253.4246

Normality


TOPSIS with lmTOP
DiA with lmTOP
MeTH with lmTOP
TOPSIS with lmMeth
DiA with lmMeth
MeTH with lmMeth
Density
Studentized Residual

Conclusions & Next Steps

Conclusions:

1. Easy to use evaluation methodology;
2. Evaluation based on statistical analysis;
3. Evaluation that promotes comparison between MADM techniques;
4. Evaluation that considers all the steps of MADM.

Next Steps:

- Apply the evaluation methodology to compare with several techniques (GRA, AHP, ELECTRE, VIKOR, etc).

http://mcoa.dei.uc.pt/doe/index.html

Thank You