ASSESSING COMPUTER NETWORK EFFICIENCY USING DEA AND MCDA TECHNIQUES

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ABSTRACT

Measuring computer network efficiency is of great importance for a network manager. When a detailed picture of the current state of the network is available, we can use analytical and simulated-based methods. Instead, it is more difficult to measure network efficiency, when the details of network topologies and internal characteristics are not available. In this paper, we present operations research techniques, which have been used in measuring efficiency of economic systems, namely Data Envelopment Analysis (DEA), Stochastic Frontier Analysis (SFA) and Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE). We investigate whether these techniques can be used to assess network efficiency and provide the network manager with a complete set of quantitative suggestions towards relative efficiency improvement of the networks determined as inefficient. The average efficiencies extracted in our benchmark from DEA and SFA are almost equal. Furthermore, the decision maker can adjust the weights of the criteria in PROMETHEE in order to build different scenarios. Consequently, we claim that these methods can be used for measuring computer network efficiency, when networks' internal characteristics are not available.

KEYWORDS

Efficiency, Computer Network, Data Envelopment Analysis, Stochastic Frontier Analysis, Multicriteria Decision Analysis.

1. Introduction

Computer networks have grown exponentially over the last decades, having become an essential part of typical business and state infrastructure. Networking is present in both small and large organizations providing a plethora of services through the deployment of multiple networks, often interconnected together. At present, computer networks are able to provide not only 'simple' file transfer and e-mail services, but also more demanding ones, such as timely delivery of real-time voice and video. In essence, they have managed to integrate old services and provide new ones under a single platform in a cost-effective way.

The focus of early networks was the support of basic connectivity in order to share expensive resources such as a printer among a growing number of users, whose computers had limited capabilities. Consequently, the network provider tended to view a network in a more 'nuts and bolts' way. As computers and computer networks evolved, however, that focus shifted towards a 'service' view: a computer network has a communications infrastructure, enabling distributed applications through communication services typically offering reliable or 'best-effort' (unreliable) data delivery from source to destination (Kurose and Ross, 2009). Hence, a computer network is seen at present as a platform offering various levels of services to the end users.

Nevertheless, network analysis, planning, design and deployment are rather complex tasks, since there are many factors the designer must take into consideration. For example, network managers have traditionally focused their attention on capacity planning, which essentially means over-engineering a network to provide an amount of capacity (usually known as bandwidth) estimated to accommodate most short- and long-term traffic fluctuations over the life cycle of the design (McCabe, 2007). This leads to the existence of a capacity 'surplus buffer' capable of handling such fluctuations. However, network growth over time can lead to the reduction of this buffer, thus making users experience congestion and inefficient uses of network resources. Furthermore, aspects such as network delay, reliability, maintainability, and availability are but some of those that need to be considered and possibly re-estimated periodically. In all cases, the first step towards successful network design is network analysis with network efficiency as the overall goal, taking into consideration both technical and economic factors.

In this paper, we examine both appropriate methods for network evaluation, as well as appropriate metrics. We employ three primary operations research techniques for measuring network efficiency, i.e. Data Envelopment Analysis (DEA), Stochastic Frontier Analysis (SFA) and Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE). These methods have been widely used in measuring efficiency of different sectors, e.g. Food Industry (Stiakakis and Sifaleras, 2010), ICT Industry (Stiakakis and Sifaleras, 2013), Transportation Industry (Hilmola, 2007) etc. We argue that these methods can be used to assess the relative efficiency of a collection of networks simultaneously, provided that certain simple conditions are met. Furthermore, a number of alternative DEA models are examined in this paper, in order to explore all improvement suggestions.

We have examined a number of parametric, non-parametric and multicriteria decision analysis techniques. We used three different alternative DEA models in order to gain all useful information that the method can offer to network managers. These models are: (i) CCR DEA, (ii) SYS DEA, and (iii) Super-efficiency DEA. First of all, we have applied the basic CCR DEA model (Charnes et al., 1984) with an input orientation in order to compare the efficiencies of Decision Making Units (DMUs) with the efficiencies extracted by the application of SFA. Furthermore, we have used the differentiated DEA model (SYS-DEA) that can be applied to examine whether the results have been affected by the different inherent characteristics of different DMUs categories. SYS-DEA can be applied not only to evaluate the efficiency of each DMU, but also to compare the two groups (universities and TEIs) by observing the efficiency of DMUs in each group. A drawback of the two aforementioned DEA models is that they cannot export a full ranking of the examined DMUs. In this case, the super-efficiency DEA model (Andersen and Petersen, 1993) can be used in order to provide a full ranking of DMUs. Finally, we have choose PROMETHEE against other multicriteria methods for two main reasons: (i) different preference functions can be defined for criteria in PROMETHEE method, and (ii) it provides a visual and powerful tool called Geometrical Analytic for Interactive Aid (GAIA) plane to group alternatives.

The remainder of this paper is organized as follows: frontier approaches to assess efficiency, a brief description of DEA and SFA techniques, and a brief overview of PROMETHEE method are presented in Section 2. In Section 3, an overview of network analysis is performed. This is followed in Section 4 by our approach in detail, using a specific group of networks as our test bed. We also present an analysis of the results produced by our approach and discuss the merits of these methods in computer networks in Section 4. Finally, conclusions are discussed in Section 5.

2. Operations research techniques to measure efficiency

2.1 Non-parametric and parametric approaches

Numerous techniques to estimate efficiency have been developed over the past 50 years. Frontier methods are the most widely applied techniques. These techniques compute the efficient frontier, which shows the distance of an observation from the 'best practice' frontier. The efficient frontier is determined by the most efficient observations. Frontier methods can be divided into parametric and non-parametric (for a literature survey, see Berger et al., 1997). Parametric methods determine efficiency of an organization against a 'best practice' frontier, while non-parametric methods evaluate the efficiency of an observation relative to other DMUs. A DMU is every observation of the data set.

The major parametric method is SFA. SFA is a stochastic parametric method that decomposes error into two distinct parts: inefficiency and a random element, assumed to be normally distributed (Rosko et al., 2008). Based on Farrell's (1957) theory, Aigner et al. (1977) and Meeusen et al. (1977) independently constructed an error structure of SFA to measure productive efficiency. Assuming the case of Cobb-Douglas production function, the SFA model can be written as:

$$\ln y_i = \ln \beta_0 + \sum_{j=1}^{k} \beta_j \ln x_{ij} + v_i - u_i$$

where v_i is the random element with the normal distribution $N(0,\sigma_v^2)$ and u_i is the non-negative efficiency of the error term with the non-negative half normal distribution $N(0,\sigma_u^2)$. Error components v_i and u_i are independent of each other, and of the regressors. The distribution of u_i is usually assumed to be non-negative half normal, truncated normal, exponential or gamma (Kumbhakar et al., 2000).

On the other hand, the most widely applied non-parametric method is DEA. DEA is a non-parametric method to measure the efficiency of a set of observations. It is based on Farrell's (1957) theory and was first introduced by Charnes et al. (1978). DEA does not require any assumption for the functional form that relates inputs to outputs. DEA constructs a discrete piecewise frontier over the observations and calculates the relative efficiency for each DMU in relation to all other DMUs. The relative efficiency of any DMU is calculated by the ratio of a weighted sum of *m* outputs over a weighted sum of *n* inputs. The weights are calculated so that the efficiency of each DMU is maximized, subject to the constraint that no DMU can have a relative efficiency greater that unity (Cooper et al., 2007). The relative efficiency for each DMU_i is the solution of the following mathematical problem:

$$\max_{u,v} (u^T \cdot y_i) / (v^T \cdot x_i)$$

$$\text{subject to} \quad (u^T \cdot y_j) / (v^T \cdot x_j) \le 1 \qquad \forall j = 1, 2, \ldots, k$$

$$u, v \ge 0$$

where u is an m x 1 vector of output weights, v is an n x 1 vector of input weights, y is an m x 1 vector of output values, x is an n x 1 vector of input values, and k is the number of DMUs.

After transforming the above fractional problem into a linear programming problem by equating the denominator of the efficiency ratio of the DMU under study to unity and using the equivalent dual model, the DEA problem can be written in the following form, namely the envelopment form:

$$\begin{aligned} &\min_{\theta,\lambda} \theta \\ \text{subject to} \quad & -y_i + Y \cdot \lambda \geq 0 \\ & \theta \cdot x_i - X \cdot \lambda \geq 0 \\ & \lambda \geq 0 \end{aligned}$$

where θ is the efficiency of DMU$_i$ ($0 < \theta \leq 1$), λ is a k x 1 vector of constants, Y is the m x k output matrix, and X is the n x k input matrix. The number of DMUs should be considerably larger than the sum of input and output items.

2.2 Multicriteria decision analysis methodologies

Multicriteria Decision Analysis (MCDA) is a subdiscipline of operations research dealing with decision problems that use multiple criteria in order to determine the best possible action. Decision makers compare different action with several objectives in mind. The deployment of a MCDA method is a non-linear recursive process consisting of several stages. Although each MCDA approach has a different number of stages, we can outline the major steps of a MCDA approach: (i) Identification of the decision problem, (ii) Identification of the decision criteria, (iii) Identification of the different alternatives, (iv) Assignment of weights to the selected criteria, and (v) Overall assessment for each action. Several methods have been proposed over the years (Goodwin and Wright, 2004); the most popular of them are Analytic Hierarchy Process (AHP) (Saaty, 1986; Saaty, 1990) and Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) (Brans, 1982; Brans and Vincke, 1985; Brans and Mareschal, 1994).

PROMETHEE is a multicriteria decision making methodology that has been applied to solve several multicriteria decision problems. The application of PROMETHEE requires two additional types of information: (i) the weights of the chosen criteria, and (ii) the preference function that the decision maker uses to compare different alternatives. The weights can be determined by applying various methods (Nijkamp et al., 1990). PROMETHEE assumes that the decision maker weighs the criteria appropriately. The preference function translates the difference between the evaluations of two alternatives in terms of a particular criterion into a preference degree ranging from 0 to 1. Six basic types have been proposed to select a specific preference function (Brans, 1982; Brans and Vincke, 1985; Brans and Mareschal, 1994).

3. Network efficiency

Network efficiency is a general and rather vague term. It can represent different things to different parties. For example, a client may consider a certain network efficient in terms of the throughput achieved regarding network services that he has asked for. On the other hand, an Internet Service Provider (ISP) may consider its network efficient, when the required volume of traffic is slightly smaller than the traffic offered by the network itself; this satisfies the clients and utilizes almost the entire available infrastructure. It is also possible to consider network efficiency in terms of a multitude of characteristics, such as minimizing the number of client requests rejected over a certain period of time, the amount of traffic which represents dropped packets due to congestion, the traffic dropped due to non-conformity to certain Quality of Service (QoS) constraints, etc.

In terms of economics, efficiency is the ratio of output over input (Cooper et al., 2007). Applying this definition in the case of computer networks one could remark that networks convey traffic and do not produce any goods or services. This, however, is not true. As an example, consider the case of a user who uses a typical web browser, asking for a particular file from a web server. The browser generates the appropriate traffic (for the file request), which is transported up to the other end of a network (or even the Internet), where there is a host computer hosting the corresponding web server. The latter finds the requested file and generates the appropriate network traffic to carry the file across the network back to the user's host. A much smaller amount of control traffic is usually generated both by the communicating hosts, as well as the intermediate routers (e.g., ICMP messages).

From this brief discussion it is clear that computer networks do produce and consume traffic, instead of merely transporting it. In this respect, network efficiency can be considered (in its simplest form) as the use of resources so as to maximize the production of network traffic.

In general, there are two typical approaches used to measure network efficiency: analytical and simulation-based. Under the analytical approach, there is a detailed knowledge of the network topology, the nature of the traffic present in the network, and the capacity of all nodes involved. The traffic demand itself (generated by the users) is random, but it is possible to model it, if it demonstrates an appropriate statistical property. Armed with this information, the network manager can employ probabilistic modeling techniques in order to evaluate the performance of a specific system. In the case of the Internet, empirical studies have shown that it can be described as self-similar traffic that can have heavy tail distribution (Willinger and Paxson, 1998). This is in contrast to the typical Poisson distribution used for telephone networks. Still, this view is contested by other researchers (Zhang et al., 2003).

Analytical models can be broadly classified into state space models represented today by Markov chains or non-state space models, such as product-form queuing networks. A Markov chain consists of a set of states and a set of labeled transitions between the states. This can be used to predict the behavior of a system, apart from evaluating its performance. For large and complex systems, such a model is more difficult to create and solve, although recent research efforts have led to the development of suitable software tools. In spite of these advances, there is a continuing need to deal with larger Markov chains and much research is being devoted to this topic (Bolch et al., 2006).

Under the simulation-based approach, an abstract model of the actual system is created and run with the desired parameters. The main drawback is the time taken to run such models for large, realistic systems. Moreover, the accuracy of the results depends on the accuracy of the models constructed.

Nevertheless, apart from considering efficiency as an absolute term, it is often useful to consider it as a relative term. In this respect, a large organization in charge of many peripheral networks may periodically assess their relative efficiency, applying the same or even different weights to account for special conditions present in some or all of these networks. This approach has the advantage that it may be simpler to implement, since ratios of various quantities may be more readily available or easier to calculate than the absolute values of these quantities.

4. Network efficiency metrics

4.1 Introduction

The first step towards evaluating computer network efficiency is to define a set of appropriate metrics offering an objective rather a subjective assessment. The main metrics used in the literature for measuring network efficiency are (RFC2330, 1998; RFC2681, 1999; Evans and Filsfils, 2007): i) propagation delay of a link, ii) bandwidth of a link for packets of size *k*, iii) route, iv) hop count of a route, v) delay, vi) delay variation or jitter, vii) packet loss, viii) throughput, ix) service availability, x) per flow sequence preservation, and xi) Round Trip Time (RTT).

Considering the above we conclude that these are the main metrics for measuring network efficiency. Nevertheless, we must take one additional factor into consideration: metric measurements availability.

The simplest view of network activity is the set of input and output traffic over a certain period of time. For large, interconnected networks that have similar link capacity and users with similar traffic demands, such measurements can even be used for comparative evaluation. As the case of the popular MRTG traffic load measurement application demonstrates (MRTG, 2012), such types of measurements are commonly used as metrics for network traffic. Measurements span a day, week, month and a year period. In the latter case MRTG averages data over a day period. Furthermore, MRTG can measure traffic in terms of packets per second, but given that IP networks allow packets of varying size we do not consider such data accurate enough for our purposes. We believe that a one-year period is the most appropriate for such measurements because it is long enough to span a complete behavior of a human society, yet reasonably small enough to assume that the networks under study have not undergone dramatic modifications in the meantime. Such a choice allows for typical cases of inactivity such as holidays and summer vacations.

Consequently, we propose the use of at least four metrics for calculating network efficiency. These metrics are input and output traffic averaged over a one-year period, and maximum input and output traffic over the same period. The input and maximum input traffic are considered as inputs, whereas the rest are considered as outputs for reasons obvious from the discussion above. Maximum input and output traffic also indicate the degree by which a network can accommodate for cases where strict timely delivery is important, but represent a small fraction of the overall traffic. Given that most of network packets are lost due to congestion, a peak traffic volume is a good indication whether such user demands are satisfied, provided that these do not aggregate close to the available bandwidth.

4.2 Test networks and metrics used

For our case study we selected a sizeable group of interconnected networks for which the relevant measurements are publicly available. These networks are all part of GRNet (Greek Research & technology Network). GRNet is a backbone network that connects the networks of all Greek universities, Technological

Educational Institutes (TEIs), and various other state organizations. The NOC (Network Operations Center) of each university or TEI does not necessarily provide the complete topology or even traffic statistics regarding its internal network. Actually, we found only a handful of such descriptions and with varying degree of detail. However, GRNet does provide diagrams with traffic measurements regarding its nodes via MRTG (GRNet, 2012). Some of the measurements refer to the main links connecting GRNet with the respective university and TEI networks. Hence, it is possible to collect real-world measurements for average and maximum input and output traffic.

Apart from the four basic metrics described earlier, there are other metrics that could be used in principle, such as the number of academic staff and the number of students.

The number of academic staff is typically used as input for such DMUs. In the case of TEIs, however, the majority of the academic staff is contracted part-time for up to nine months during each academic year, most of which offer laboratory assistance. Therefore, these figures represent non-homogenous populations and using them could lead to inaccurate results.

On the other hand, the numbers of registered students for all the respective DMUs represent populations with similar behavior patterns as far as network usage is concerned. They are by far the largest consumer group of network traffic and tend to use mostly web, mail and file transfer services. Hence, they represent an output metric for our DMUs, since they typically consume more traffic than they produce.

We compared the proposed five metrics from 25 academic institutions. Most of these networks have a 1 Gbps main link to the GRNet backbone, with the rest having 2.5 Gbps and 10 Gbps, respectively. In this sense, the main link capacities fall within an order of magnitude. Furthermore, the input or output traffic is never close to the respective network link capacity which indicates that these measurements were not affected by link bandwidth limitations. The same holds for the number of students, since the respective figures differ by at most an order of magnitude. Table 1 summarizes the data collected according to our selected metrics for each network.

Table 1. Networks and respective metrics

	Inputs		Outputs		
University/TEI (DMU)	Traffic In (Mbps)	Max Traffic In (Mbps)	Traffic Out (Mbps)	Max Traffic Out (Mbps)	No. of Students
NTUA	175.20	1018.70	920.90	2218.20	8,858
UoAthens	115.60	579.80	344.90	960.00	32,335
AUTH	89.20	2453.50	206.90	650.00	34,148
AUEB	26.10	534.40	68.20	345.10	6,857
UoPatras	669.70	924.20	267.90	279.60	12,993
UoCrete	91.80	775.50	436.70	1150.00	8,421
UoIoannina	60.00	552.20	105.80	8020	10,451
DUTh	28.30	410.00	88.30	686.30	11,732
UoPeloponnese	0.54	93.10	48.90	292.70	2,519
UoMacedonia	19.70	284.80	48.70	415.20	5,889
UoWesternMacedonia	3.80	327.80	17.20	149.80	2,340
Tech. UoCrete	41.60	215.30	146.60	709.40	1,973
TEI Athens	69.10	1460.00	24.20	248.09	15,838
TEI Patras	10.70	117.00	39.20	199.50	10,218
TEI Larisa	11.00	101.80	7.07	914.30	9,928
TEI Lamia	3.22	61.30	6.310	40.60	3,989
TEI Halkis	1.00	101.00	0.39	11.60	5,460

TEI Kalamata	0.87	48.00	3.70	52.30	2,772
TEI Serres	5.25	99.90	9.44	99.80	5,600
TEI Thessaloniki	10.70	941.20	5.56	413.70	12,334
TEI Kozani	12.60	99.70	16.80	99.50	9,931
TEI Ionian Islands	0.68	3.58	0.66	7.37	2,023
TEI Messolongi	2.09	92.50	0.54	733.20	4,049
TEI Crete	38.20	983.20	132.60	348.10	9,322
TEI Kavala	14.20	133.70	25.80	188.60	5,444

4.3 Results

4.3.1 CCR DEA

Network efficiencies with DEA have been computed using DEA-Solver v6.0 (Saitech, 2014), a commercial software package by SAITECH, Inc. We have examined a number of alternative DEA models in order to gain all useful information that the method can offer to network managers. We first applied the CCR DEA model (Charnes et al., 1984) with an input orientation in order to compare the efficiencies of DMUs with the efficiencies extracted by the application of SFA. The CCR DEA model is a Variable Returns to Scale (VRS), meaning that a proportional increase in all inputs will result in an increase of the output, but not at the same proportion. As an example, consider the case of a typical file transfer. The user generates a small amount of traffic to request one or more files (e.g., a video or a document). For every large chunk of file downloaded the user's file transfer application automatically sends a small acknowledgement to signal correct delivery. The overall user traffic volume is very small compared to the one generated by the server which transmits the requested files.

Of the 25 universities and TEIs, 6 are efficient DMUs, according to the results of the CCR DEA model. The average efficiency score is 0.57, the minimum 0.07, and the standard deviation 0.32. Table 2 presents the score and rank of each university and TEI, while Table 3 shows the differences between the actual and the expected values only for the inefficient DMUs. These differences represent the required reductions for each of the input items, as well as the required increases for output items.

Table 2. Score and rank using CCR DEA

UNIVERSITY/TEI	No.	DMU	Score	Rank	Reference set (lambda)
NTUA	1	A	1	1	A
UoAthens	2	B	0.73	10	A
AUTH	3	C	0.16	23	A
AUEB	4	D	0.22	22	A
UoPatras	5	E	0.34	18	A
UoCrete	6	F	0.72	11	A
UoIoannina	7	G	1	1	G
DUTh	8	H	0.40	13	A
UoPeloponnese	9	I	1	1	I
UoMacedonia	10	J	0.32	19	A
UoWesternMacedonia	11	K	0.16	24	I
Tech. UoCrete	12	L	0.85	7	A
TEI Athens	13	M	0.07	25	I
TEI Patras	14	N	0.61	12	A
TEI Larisa	15	O	0.81	8	G

TEI Lamia	16	P	0.39	14	I
TEI Halkis	17	Q	1	1	Q
TEI Kalamata	18	R	0.81	9	I
TEI Serres	19	S	0.34	17	I
TEI Thessaloniki	20	T	0.26	20	I
TEI Kozani	21	U	0.38	15	A
TEI Ionian Islands	22	V	1	1	V
TEI Messolongi	23	W	1	1	W
TEI Crete	24	Y	0.23	21	A
TEI Kavala	25	Z	0.35	16	A

Table 3. Projection of inefficient DMUs onto the efficient frontier using CCR DEA

DMU	No.	DMU I/O	Score Data	Projection	Difference	%
UoAthens	2	B	0.73			
		TrafficIn	115.60	73.82	-41.78	-36.14%
		MaxTrafficIn	579.80	425.05	-154.75	-26.69%
		TrafficOut	344.90	344.90	0.00	0.00%
		MaxTrafficOut	960.00	960.00	0.00	0.00%
		Students	32335.00	32335.00	0.00	0.00%
AUTH	3	C	0.16			
		TrafficIn	89.20	14.69	-74.51	-83.53%
		MaxTrafficIn	2453.50	404.08	-2049.42	-83.53%
		TrafficOut	206.90	206.90	0.00	0.00%
		MaxTrafficOut	650.00	1197.96	547.96	84.30%
		Students	34148.00	34148.00	0.00	0.00%
AUEB	4	D	0.22			
		TrafficIn	26.10	5.80	-20.30	-77.78%
		MaxTrafficIn	534.40	118.73	-415.67	-77.78%
		TrafficOut	68.20	68.20	0.00	0.00%
		MaxTrafficOut	345.10	345.10	0.00	0.00%
		Students	6857.00	6857.00	0.00	0.00%
UoPatras	5	E	0.34			
		TrafficIn	669.70	53.83	-615.87	-91.96%
		MaxTrafficIn	924.20	311.07	-613.13	-66.34%
		TrafficOut	267.90	267.90	0.00	0.00%
		MaxTrafficOut	279.60	675.15	395.55	141.47%
		Students	12993.00	12993.00	0.00	0.00%
UoCrete	6	F	0.72			
		TrafficIn	91.80	66.17	-25.63	-27.92%
		MaxTrafficIn	775.50	559.01	-216.49	-27.92%
		TrafficOut	436.70	436.70	0.00	0.00%
		MaxTrafficOut	1150.00	1391.50	241.50	21.00%
		Students	8421.00	8421.00	0.00	0.00%
DUTh	8	H	0.40			
		TrafficIn	28.30	11.40	-16.90	-59.73%
		MaxTrafficIn	410.00	165.09	-244.91	-59.73%
		TrafficOut	88.30	88.30	0.00	0.00%
		MaxTrafficOut	686.30	686.30	0.00	0.00%
		Students	11732.00	11732.00	0.00	0.00%
UoMacedonia	10	J	0.32			
		TrafficIn	19.70	6.37	-13.33	-67.64%
		MaxTrafficIn	284.80	92.15	-192.65	-67.64%
		TrafficOut	48.70	48.70	0.00	0.00%

		MaxTrafficOut	415.20	415.20	0.00	0.00%
		Students	5889.00	5889.00	0.00	0.00%
UoWesternMacedonia	11	K	0.16			
		TrafficIn	3.80	0.60	-3.20	-84.17%
		MaxTrafficIn	327.80	51.89	-275.91	-84.17%
		TrafficOut	17.20	24.72	7.52	43.72%
		MaxTrafficOut	149.80	149.80	0.00	0.00%
		Students	2340.00	2340.00	0.00	0.00%
Tech. UoCrete	12	L	0.85			
		TrafficIn	41.60	29.75	-11.85	-28.48%
		MaxTrafficIn	215.30	182.30	-33.00	-15.33%
		TrafficOut	146.60	146.60	0.00	0.00%
		MaxTrafficOut	709.40	709.40	0.00	0.00%
		Students	1973.00	1973.00	0.00	0.00%
TEI Athens	13	M	0.07			
		TrafficIn	69.10	4.96	-64.14	-92.82%
		MaxTrafficIn	1460.00	104.85	-1355.15	-92.82%
		TrafficOut	24.20	37.46	13.26	54.77%
		MaxTrafficOut	248.09	248.09	0.00	0.00%
		Students	15838.00	15838.00	0.00	0.00%
TEI Patras	14	N	0.61			
		TrafficIn	10.70	6.58	-4.12	-38.51%
		MaxTrafficIn	117.00	71.95	-45.05	-38.51%
		TrafficOut	39.20	39.20	0.00	0.00%
		MaxTrafficOut	199.50	199.50	0.00	0.00%
		Students	10218.00	10218.00	0.00	0.00%
TEI Larisa	15	O	0.81			
		TrafficIn	11.00	8.87	-2.13	-19.35%
		MaxTrafficIn	101.80	82.11	-19.69	-19.35%
		TrafficOut	7.07	12.94	5.87	83.07%
		MaxTrafficOut	914.30	914.30	0.00	0.00%
		Students	9928.00	9928.00	0.00	0.00%
TEI Lamia	16	P	0.39			
		TrafficIn	3.22	1.24	-1.98	-61.49%
		MaxTrafficIn	61.30	23.61	-37.69	-61.49%
		TrafficOut	6.00	6.00	0.00	0.00%
		MaxTrafficOut	40.60	42.23	1.63	4.02%
		Students	3989.00	3989.00	0.00	0.00%
TEI Kalamata	18	R	0.81			
		TrafficIn	0.87	0.70	-0.17	-19.41%
		MaxTrafficIn	48.00	38.68	-9.32	-19.41%
		TrafficOut	3.70	8.06	4.36	117.94%
		MaxTrafficOut	52.30	52.30	0.00	0.00%
		Students	2772.00	2772.00	0.00	0.00%
TEI Serres	19	S	0.34			
		TrafficIn	5.25	1.80	-3.45	-65.69%
		MaxTrafficIn	99.90	34.28	-65.62	-65.69%
		TrafficOut	9.44	14.89	5.45	57.73%
		MaxTrafficOut	99.80	99.80	0.00	0.00%
		Students	5600.00	5600.00	0.00	0.00%
TEI Thessaloniki	20	T	0.26			
		TrafficIn	10.70	2.78	-7.92	-74.01%
		MaxTrafficIn	941.20	244.61	-696.59	-74.01%
		TrafficOut	5.56	66.57	61.01	999.90%
		MaxTrafficOut	413.70	413.70	0.00	0.00%

		Students	12334.00	12334.00	0.00	0.00%
TEI Kozani	21	U	0.38			
		TrafficIn	12.60	4.74	-7.86	-62.38%
		MaxTrafficIn	99.70	37.51	-62.19	-62.38%
		TrafficOut	16.80	16.80	0.00	0.00%
		MaxTrafficOut	99.50	99.50	0.00	0.00%
		Students	9931.00	9931.00	0.00	0.00%
TEI Crete	24	Y	0.23			
		TrafficIn	38.20	8.93	-29.27	-76.63%
		MaxTrafficIn	983.20	229.74	-753.46	-76.63%
		TrafficOut	132.60	132.60	0.00	0.00%
		MaxTrafficOut	348.10	678.02	329.92	94.78%
		Students	9322.00	9322.00	0.00	0.00%
TEI Kavala	25	Z	0.35			
		TrafficIn	14.20	4.99	-9.21	-64.87%
		MaxTrafficIn	133.70	46.97	-86.73	-64.87%
		TrafficOut	25.80	25.80	0.00	0.00%
		MaxTrafficOut	188.60	188.60	0.00	0.00%
		Students	5444.00	5444.00	0.00	0.00%

As a result, the above tables should be considered as a guide for network managers of these organizations in order to suggest exactly which items, and to what extent, need to be improved to achieve operational efficiency. For instance, ‘Max Traffic Out’ for the UoPatras should be increased so that the relative efficiency of the respective network improves. In order to visualize these suggestions, Figures 1 - 5 have been drawn. Figure 1 shows the ideal curve of the efficient DMUs for TrafficIn and the difference from TrafficIn for UoPatras. Figures 2, 3, 4 and 5 show the ideal curve for MaxTrafficIn, TrafficOut, MaxTrafficOut and StudentsNo, respectively. We stress, however, that this guide determines only what should be done; not the actual means to achieve it. For example, the network manager may decide to install a mirror server for popular files (e.g., software, videos, etc.), making more bandwidth available to it at specific time periods, in order to increase output traffic.

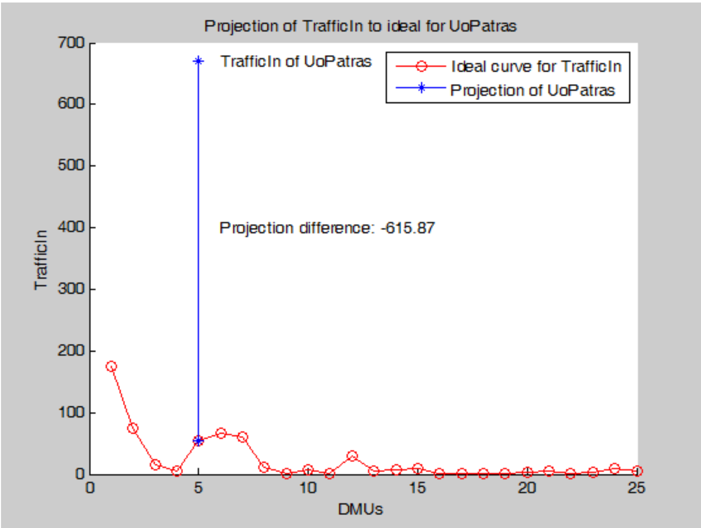

Figure 1. Projection of TrafficIn to ideal for UoPatras

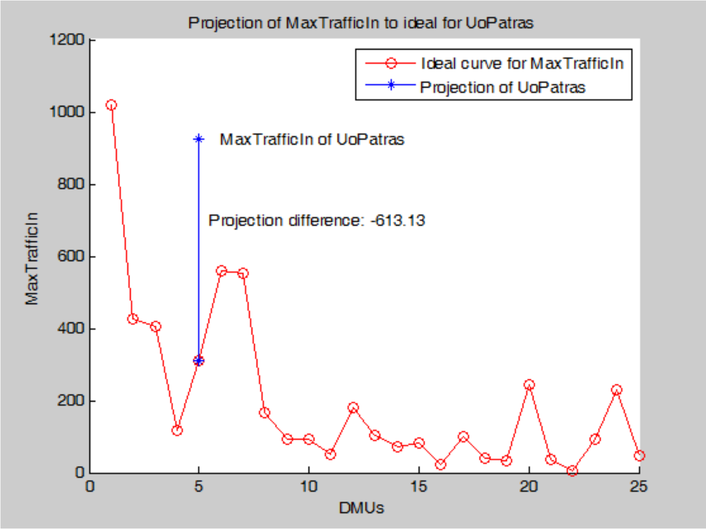

Figure 2. Projection of MaxTrafficIn to ideal for UoPatras

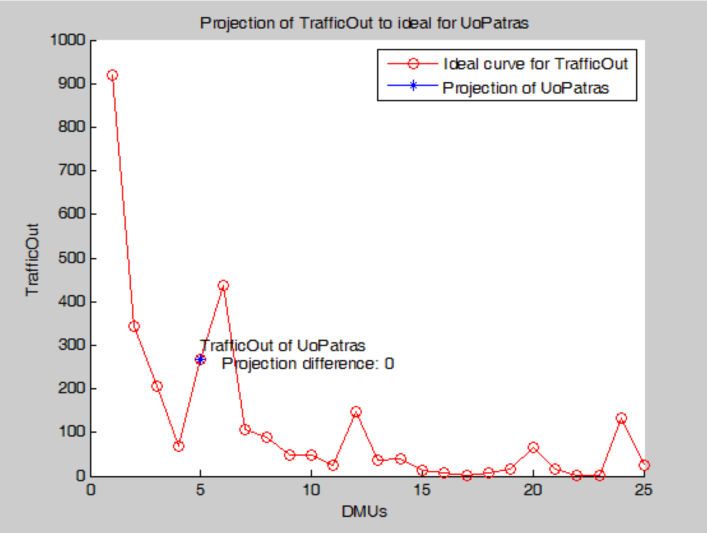

Figure 3. Projection of TrafficOut to ideal for UoPatras

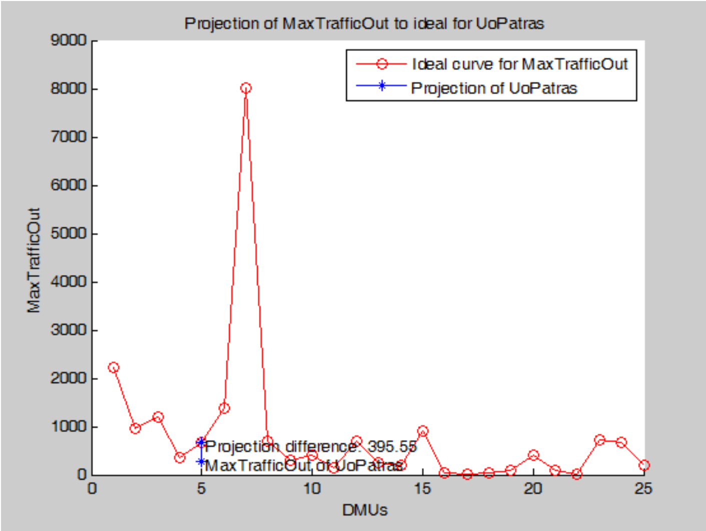

Figure 4. Projection of MaxTrafficOut to ideal for UoPatras

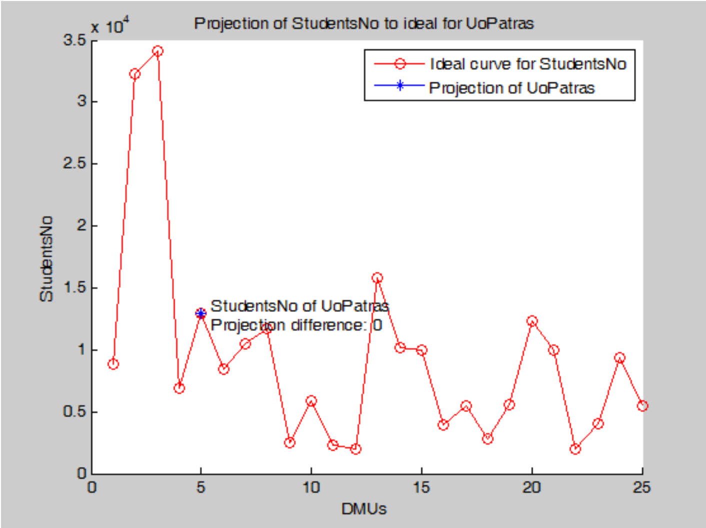

Figure 5. Projection of StudentsNo to ideal for UoPatras

The figures above can be used as performance targets for UoPatras. However, in the real world, it is not possible for the network manager of UoPatras to adjust all inputs and outputs of his network for it to become efficient. Therefore, some efficiency improvement approaches should be used for each DMU to possess an efficiency improvement plan. In this paper, we employ the efficiency improvement algorithm proposed by Alirezaee and Afsharian (2009), illustrated by an example below. At first we run the CCR input-oriented model and calculate the input and output elasticities for each DMU. Elasticity shows the relationship between the quantities of an input or output variable and the efficiency of a DMU. The elasticity of a specific variable depicts the ratio of the percentage change in the efficiency of a DMU to the percentage change in this variable. Table 4 presents the elasticities for all DMUs in our case study.

Table 4. Input and output elasticities for each DMU

UNIVERSITY/TEI	No.	E-TrafficIn	E-MaxTrafficIn	E-TrafficOut	E-MaxTrafficOut	E-Students
NTUA	1	0.43	0.57	1.00	0.00	0.00
UoAthens	2	0.00	1.00	0.86	0.14	0.00
AUTH	3	0.12	0.88	1.00	0.00	0.00
AUEB	4	0.11	0.89	0.81	0.19	0.00
UoPatras	5	0.00	1.00	1.00	0.00	0.00
UoCrete	6	0.31	0.69	1.00	0.00	0.00
UoIoannina	7	0.57	0.43	0.00	1.00	0.00
DUTh	8	0.15	0.85	0.73	0.27	0.00
UoPeloponnese	9	1.00	0.00	1.00	0.00	0.00
UoMacedonia	10	0.16	0.84	0.71	0.29	0.00
UoWesternMacedonia	11	0.56	0.44	0.00	0.24	0.76
Tech. UoCrete	12	0.00	1.00	0.78	0.22	0.00
TEI Athens	13	0.84	0.16	0.00	1.00	0.00
TEI Patras	14	0.20	0.80	0.63	0.15	0.22
TEI Larisa	15	0.48	0.52	0.00	0.74	0.26
TEI Lamia	16	0.85	0.15	0.04	0.00	0.96
TEI Halkis	17	1.00	0.00	0.00	0.00	1.00
TEI Kalamata	18	0.67	0.33	0.00	0.09	0.91
TEI Serres	19	0.83	0.17	0.00	0.11	0.89
TEI Thessaloniki	20	0.56	0.44	0.00	0.14	0.86

TEI Kozani	21	0.25	0.75	0.48	0.13	0.39
TEI Ionian Islands	22	0.95	0.05	0.00	0.02	0.98
TEI Messolongi	23	0.81	0.19	0.00	1.00	0.00
TEI Crete	24	0.13	0.87	1.00	0.00	0.00
TEI Kavala	25	0.22	0.78	0.61	0.21	0.18

For instance, input elasticities for UoMacedonia are 0.16 and 0.84, respectively, and output elasticities 0.71, 0.29 and 0, respectively. According to these values, MaxTrafficIn and TrafficOut are effective factors on efficiency changes for UoMacedonia among all inputs and outputs, respectively.

In order to illustrate the way that the network manager of UoMacedonia can make an appropriate strategic plan for performance improvement, let us consider the following two scenarios, after calculating the elasticities above: i) increase the efficiency of UoMacedonia by 0.10 changing only the input variables, and ii) increase the efficiency of UoMacedonia by 0.40 changing only the outputs.

Scenario 1: By applying the algorithm of Alirezaee and Afsharian (2009), we first calculate the proportional efficiency changes for each input variable:

$$\Delta Eff = 0.10 \begin{cases} \rightarrow \Delta Eff_{TrafficIn} = ex_{TrafficIn} * 0.10 = 0.16 * 0.10 = 0.016 \\ \rightarrow \Delta Eff_{MaxTrafficIn} = ex_{MaxTrafficIn} * 0.10 = 0.84 * 0.10 = 0.084 \end{cases}$$

where ex_i is the input elasticity for variable i and ΔEff_i is the proportional efficiency changes for variable i.

Then, we calculate the changes in input variables:

$$\Delta x_i = \frac{x_i * \Delta Eff}{Eff * ex_i} \begin{cases} \rightarrow \Delta x_{TrafficIn} = \frac{19.7 * 0.016}{0.32 * 0.16} = 6.1562 \\ \rightarrow \Delta x_{MaxTrafficIn} = \frac{284.8 * 0.084}{0.32 * 0.84} = 89 \end{cases}$$

where x_i is the value of the DMU for variable i, Δx_i is the change for variable i and Eff is the efficiency of the DMU.

By subtracting input changes from the old input values, we end up with the new values for TrafficIn and MaxTrafficIn:

$$x_i(new) = x_i - \Delta x_i \begin{cases} \rightarrow x_{TrafficIn}(new) = 19.7 - 6.1562 = 13.5438 \\ \rightarrow x_{MaxTrafficIn}(new) = 284.8 - 89 = 195.8 \end{cases}$$

These are the new values that the input variables should acquire in order to increase the efficiency of UoMacedonia by 0.10.

Scenario 2: The proportional efficiency changes for each output variable are calculated first:

$$\Delta Eff = 0.40 \begin{cases} \rightarrow \Delta Eff_{TrafficOut} = ex_{TrafficOut} * 0.40 = 0.71 * 0.40 = 0.2840 \\ \rightarrow \Delta Eff_{MaxTrafficOut} = ex_{TrafficOut} * 0.40 = 0.29 * 0.40 = 0.1160 \\ \rightarrow \Delta Eff_{Students} = 0 * 0.40 = 0 \end{cases}$$

Then, the changes in output variables:

$$\Delta y_i = \frac{y_i * \Delta Eff_i}{Eff * ey_i} \begin{cases} \rightarrow \Delta y_{TrafficOut} = \frac{48.7 * 0.2840}{0.32 * 0.71} = 60.8750 \\ \rightarrow \Delta y_{MaxTrafficOut} = \frac{415.2 * 0.1160}{0.32 * 0.29} = 519 \\ \rightarrow \Delta y_{Students} = 0 \end{cases}$$

Finally, we end up with the new values for TrafficOut and MaxTrafficOut, by adding output changes with old outputs:

$$y_i(new) = y_i + \Delta y_i \quad \begin{array}{l} \rightarrow y_{TrafficOut}(new) = 48.7 + 60.8750 = 109.5750 \\ \rightarrow y_{MaxTrafficOut}(new) = 415.2 + 519 = 934.2 \\ \rightarrow y_{Students}(new) = 5889 + 0 = 5889 \end{array}$$

We have, thus, calculated the new values that the output variables should acquire in order to increase the efficiency of UoMacedonia by 0.40.

4.3.2 SYS DEA

The DMUs under consideration can be divided into the following two groups: a) universities and b) technological educational institutes (TEIs); as a result, system differentiated DEA (SYS-DEA), which is another DEA model, can be applied to examine whether the results have been affected by the different inherent characteristics of universities (DMUs 1 – 12) and TEIs (DMUs 13 – 25). SYS-DEA is appropriate when the DMUs exhibit systematic differences and can be classified into categories (Yang, 2009). A network manager can apply SYS-DEA not only to evaluate the efficiency of each DMU, but also to compare the two groups by observing the efficiency of DMUs in each group. Table 5 presents the score and rank of each university and TEI, while Table 6 shows the differences between the actual and expected values only for the inefficient DMUs.

Of the 12 universities, 6 are efficient DMUs, and the average efficiency score of universities is 0.81, the minimum 0.28, and the standard deviation 0.26. Of the 13 TEIs, 8 are efficient DMUs, and the average efficiency score of TEIs are 0.87, the minimum 0.57, and the standard deviation 0.16. The results show that each DMU that was previously efficient in CCR is still efficient, but from the 19 inefficient DMUs in CCR, 11 are still inefficient and 8 become efficient. This means that 2 DMUs, which become efficient, are not efficient compared with all universities and TEIs, but compared only with the respective universities or TEIs. Hence, if the network manager is interested to assess his network efficiency in comparison only with the networks of each group, he should apply SYS-DEA.

Table 5. Score and rank using SYS-DEA

UNIVERSITY/TEI	No.	DMU	Score	Rank	Reference set (lambda)
NTUA	1	A	1	1	A
UoAthens	2	B	1	1	B
AUTH	3	C	1	1	C
AUEB	4	D	0.52	23	B
UoPatras	5	E	0.41	24	A
UoCrete	6	F	0.92	16	A
UoIoannina	7	G	1	1	G
DUTh	8	H	1	1	H
UoPeloponnese	9	I	1	1	I
UoMacedonia	10	J	0.62	20	B
UoWesternMacedonia	11	K	0.28	25	I
Tech. UoCrete	12	L	0.96	15	A
TEI Athens	13	M	0.57	22	C
TEI Patras	14	N	1	1	N
TEI Larisa	15	O	1	1	O
TEI Lamia	16	P	0.69	19	N

TEI Halkis	17	Q	1	1	Q
TEI Kalamata	18	R	1	1	R
TEI Serres	19	S	0.70	18	N
TEI Thessaloniki	20	T	1	1	T
TEI Kozani	21	U	1	1	U
TEI Ionian Islands	22	V	1	1	V
TEI Messolongi	23	W	1	1	W
TEI Crete	24	Y	0.76	17	A
TEI Kavala	25	Z	0.62	21	N

Table 6. Projection of inefficient DMUs onto the efficient frontier using SYS-DEA

DMU	No.	DMU	Score	Projection	Difference	%
		I/O	Data			
AUEB	4	D	0.52			
		TrafficIn	26.10	13.46	-12.64	-48.44%
		MaxTrafficIn	534.40	275.53	-258.87	-48.44%
		TrafficOut	68.20	68.20	0	0.00%
		MaxTrafficOut	345.10	451.19	106.09	30.74%
		Students	6857	6857	0	0.00%
UoPatras	5	E	0.41			
		TrafficIn	669.70	62.31	-607.39	-90.70%
		MaxTrafficIn	924.20	380.95	-543.25	-58.78%
		TrafficOut	267.90	267.90	0	0.00%
		MaxTrafficOut	279.60	780.68	501.08	179.21%
		Students	12993	12993	0	0.00%
UoCrete	6	F	0.92			
		TrafficIn	91.80	84.02	-7.78	-8.48%
		MaxTrafficIn	775.50	709.77	-65.73	-8.48%
		TrafficOut	436.70	436.70	0	0.00%
		MaxTrafficOut	1150	1150	0	0.00%
		Students	8421	8421	0	0.00%
UoMacedonia	10	J	0.62			
		TrafficIn	19.70	12.27	-7.43	-37.74%
		MaxTrafficIn	284.80	177.32	-107.48	-37.74%
		TrafficOut	48.70	73.38	24.68	50.69%
		MaxTrafficOut	415.20	415.20	0	0.00%
		Students	5889	5889	0	0.00%
UoWesternMacedonia	11	K	0.28			
		TrafficIn	3.80	0.54	-3.26	-85.79%
		MaxTrafficIn	327.80	93.10	-234.70	-71.60%
		TrafficOut	17.20	48.90	31.70	184.30%
		MaxTrafficOut	149.80	292.70	142.90	95.39%
		Students	2340	2518.98	178.97	7.65%
Tech. UoCrete	12	L	0.96			
		TrafficIn	41.60	21.38	-20.22	-48.61%
		MaxTrafficIn	215.30	207.35	-7.95	-3.69%
		TrafficOut	146.60	146.60	0	0.00%
		MaxTrafficOut	709.40	709.40	0	0.00%
		Students	1973	3427.97	1454.97	73.74%
TEI Athens	13	M	0.57			
		TrafficIn	69.10	39.22	-29.88	-43.24%
		MaxTrafficIn	1460	828.74	-631.26	-43.24%
		TrafficOut	24.20	110.82	86.62	357.93%
		MaxTrafficOut	248.09	644.95	396.86	159.96%

		Students	15838	15838	0	0.00%
TEI Lamia	16	P	0.69			
		TrafficIn	3.22	2.21	-1.01	-31.43%
		MaxTrafficIn	61.30	42.03	-19.27	-31.43%
		TrafficOut	6	6	0	0.00%
		MaxTrafficOut	40.60	40.60	0	0.00%
		Students	3989	3989	0	0.00%
TEI Serres	19	S	0.70			
		TrafficIn	5.25	3.70	-1.55	-29.60%
		MaxTrafficIn	99.90	70.33	-29.57	-29.60%
		TrafficOut	9.44	9.44	0	0.00%
		MaxTrafficOut	99.80	113.04	13.24	13.27%
		Students	5600	5600	0	0.00%
TEI Crete	24	Y	0.76			
		TrafficIn	38.20	28.89	-9.31	-24.37%
		MaxTrafficIn	983.20	627.57	-355.64	-36.17%
		TrafficOut	132.60	132.60	0	0.00%
		MaxTrafficOut	348.10	479.23	131.13	37.67%
		Students	9322	9322	0	0.00%
TEI Kavala	25	Z	0.62			
		TrafficIn	14.20	7.77	-6.43	-45.29%
		MaxTrafficIn	133.70	82.63	-51.07	-38.19%
		TrafficOut	25.80	25.80	0	0.00%
		MaxTrafficOut	188.60	188.60	0	0.00%
		Students	5444	7786.62	2342.62	43.03%

4.3.3 Super-efficiency DEA

By applying the CCR or the SYS-DEA model, it is not easy to get a full ranking of the examined DMUs. For instance, the results of the application of the CCR DEA model demonstrate that six DMUs, namely, DMU1, DMU7, DMU9, DMU17, DMU22, and DMU23 are efficient (see Table 2). Ranking among those networks is not possible, and this is a drawback of the aforementioned DEA models. A network manager would like to possess a more accurate rank for each DMU. In this case, the super-efficiency DEA model (Andersen and Petersen, 1993) can be used. This model was introduced with the objective to provide a full ranking of DMUs when the standard DEA models produce several efficient units. The super-efficiency DEA model excludes the efficient DMU under evaluation from the efficient frontier. The effect of this is to shrink the frontier, allowing the efficient DMU to become super-efficient since it now has a score greater than unity. Table 7 presents the score and rank of each university and TEI using the super-efficiency DEA model.

Table 7. Score and rank using super-efficiency DEA

UNIVERSITY/TEI	No.	DMU	Score	Rank	Reference set (lambda)
NTUA	1	A	1.2313	6	I
UoAthens	2	B	0.6426	10	A
AUTH	3	C	0.1432	24	I
AUEB	4	D	0.1612	21	I
UoPatras	5	E	0.2085	20	A
UoCrete	6	F	0.5947	11	A
UoIoannina	7	G	1.4357	4	I

DUTh	8	H	0.2993	16	I
UoPeloponnese	9	I	9.5732	1	A
UoMacedonia	10	J	0.2402	19	I
UoWesternMacedonia	11	K	0.1562	23	I
Tech. UoCrete	12	L	0.7253	8	A
TEI Athens	13	M	0.0630	25	I
TEI Patras	14	N	0.5097	12	I
TEI Larisa	15	O	0.7987	7	G
TEI Lamia	16	P	0.3318	14	I
TEI Halkis	17	Q	1.2596	5	I
TEI Kalamata	18	R	0.7072	9	I
TEI Serres	19	S	0.3185	15	I
TEI Thessaloniki	20	T	0.2461	18	I
TEI Kozani	21	U	0.3426	13	I
TEI Ionian Islands	22	V	4.5453	2	O
TEI Messolongi	23	W	1.5844	3	G
TEI Crete	24	Y	0.1600	22	I
TEI Kavala	25	Z	0.2728	17	G

4.3.4 Comparison of DEA models

Table 8 presents a comparison of the results obtained by the CCR DEA model, SYS-DEA model, and the super-efficiency DEA model.

Table 8. Comparison between CCR DEA, SYS-DEA, super-efficiency DEA

	CCR DEA		**SYS-DEA**		**Super-efficiency DEA**	
Number of efficient DMUs	6		14		6	
	Universities	TEIs	Universities	TEIs	Universities	TEIs
	3	3	6	8	3	3
Average efficiency score	0.57		0.84		1.06	
	Universities	TEIs	Universities	TEIs	Universities	TEIs
	0.58	0.56	0.81	0.87	1.28	0.86

4.3.5 Stochastic Frontier Analysis

Network efficiencies with SFA have been computed using package "Benchmarking of the R Project for Statistical Computing", a free software environment for statistical computing and graphics (The R Project for Statistical Computing, 2014). As already mentioned, one limitation of SFA models is that they can only handle one output. In order to overcome this limitation, two solutions can be adopted. The first option is to use cost functions, but these require other information, such as costs, not available in our case. The second option is to use distance functions directly on the data set and a special input variable must be selected in order to norm the left hand side of the distance expression. We have used MaxTrafficIn as the special input variable. If we used TrafficIn as the special input variable, we would get the same results. Note that it does not matter which input is used as the special input variable in the estimation (Bogetoft and Otto, 2011).

Of the 25 universities and TEIs examined, the average efficiency score is 0.49, the minimum 0.10, and the standard deviation 0.20. Table 9 presents the score and rank of each university and TEI. The average efficiency using SFA is lower than that of normal DEA, i.e. the CCR DEA model. This means that SFA has removed any random noise imported in the DEA efficiency scores. Furthermore, efficient DMUs under normal DEA also have high efficiency scores in SFA, except for the cases of TEI Halkis and TEI Messolongi. Finally, TEI Athens (with the lowest efficiency under normal DEA) is still ranked last under SFA. Compared to the results obtained from CCR-DEA, the rank of the DMUs is almost the same, so we can claim that operations research techniques, like DEA and SFA, can be utilized for assessing computer network efficiency.

Table 9. Score and rank using SFA

UNIVERSITY/TEI	No.	DMU	Score	Rank
NTUA	1	A	0.63	7
UoAthens	2	B	0.57	11
AUTH	3	C	0.20	21
AUEB	4	D	0.40	19
UoPatras	5	E	0.20	22
UoCrete	6	F	0.58	10
UoIoannina	7	G	0.65	5
DUTh	8	H	0.50	16
UoPeloponnese	9	I	0.84	1
UoMacedonia	10	J	0.56	12
UoWesternMacedonia	11	K	0.38	18
Tech. UoCrete	12	L	0.70	3
TEI Athens	13	M	0.10	25
TEI Patras	14	N	0.60	8
TEI Larisa	15	O	0.69	4
TEI Lamia	16	P	0.53	15
TEI Halkis	17	Q	0.15	24
TEI Kalamata	18	R	0.64	6
TEI Serres	19	S	0.54	14
TEI Thessaloniki	20	T	0.14	23
TEI Kozani	21	U	0.56	13
TEI Ionian Islands	22	V	0.77	2
TEI Messolongi	23	W	0.50	17
TEI Crete	24	Y	0.33	20
TEI Kavala	25	Z	0.59	9

4.3.6 PROMETHEE

The application of the PROMETHEE approach has been implemented with Visual PROMETHEE Academic (Visual Promethee, 2014). The actions are the 25 universities and TEIs and the criteria the five aforementioned metrics. All criteria are to be maximized. As discussed before, maximum input and output traffic indicate the degree by which a network can accommodate for cases where strict timely delivery is important, but represent a small fraction of the overall traffic. Hence, we assume that these two metrics are not as important as the input and output traffic. Furthermore, the least important criterion is the number of students. The criteria and alternatives for the application of PROMETHEE are shown on Figure 6.

Scenario1	TrafficIn	MaxTrafficIn	TrafficOut	MaxTrafficOut	Students
Unit	unit	unit	unit	unit	unit
Cluster/Group					
Preferences					
Min/Max	max	max	max	max	max
Weight	20,00	10,00	20,00	10,00	5,00
Preference Fn.	Usual	Usual	Usual	Usual	Usual
Thresholds	absolute	absolute	absolute	absolute	absolute
- Q: Indifference	n/a	n/a	n/a	n/a	n/a
- P: Preference	n/a	n/a	n/a	n/a	n/a
- S: Gaussian	n/a	n/a	n/a	n/a	n/a
Statistics					
Minimum	0,54	3,58	0,39	7,37	1973,00
Maximum	669,70	2453,50	920,90	8020,00	34148,00
Average	60,05	496,49	118,92	769,32	9416,96
Standard Dev.	131,61	557,12	198,98	1554,22	7958,62
Evaluations					
NTUA	175,20	1018,70	920,90	2218,20	8858,00
UoAthens	115,60	579,80	344,90	960,00	32335,00
AUTH	89,20	2453,50	206,90	650,00	34148,00
AUEB	26,10	534,40	68,20	345,10	6857,00
UoPatras	669,70	924,20	267,90	279,60	12993,00
UoCrete	91,80	775,50	436,70	1150,00	8421,00
UoIoannina	60,00	552,20	105,80	8020,00	10451,00
Duth	28,30	410,00	88,30	686,30	11732,00

Figure 6. Criteria and alternatives

Figure 7 and Figure 8 present the final rankings of all alternatives using the PROMETHEE I partial ranking and the PROMTHEE II complete ranking, respectively. In Figure 7, the left bar shows the ranking of the alternatives according to Phi+ and the rights bar the ranking according to Phi-. Table 10 shows the complete ranking of the universities and TEIs. NTUA is ranked first among all the other universities and TEIs, UoAthens, UoCrete, AUTH and UoPatras are close enough. On the other hand, TEI Ionian Islands is ranked last. Finally, the GAIA plane is shown on Figure 9. The decision maker can adjust the weights to build different scenarios and extract the advantages and disadvantages of a chosen university or TEI. Concerning the criteria used, we can identify two groups of criteria expressing similar preferences:

- TrafficIn and MaxTrafficIn are close to each other. This means that universities and TEIs having a higher input traffic level have also a higher maximum input traffic level. Such universities and TEIs are Duth, TEI Crete, UoPatras, AUTH, UoAthens, etc.
- TrafficOut and MaxTrafficOut are close to each other. This means that universities and TEIs having a higher output traffic level have also a higher maximum output traffic level. Such universities and TEIs are Duth, TEI Crete, UoPatras, AUTH, UoAthens, etc. Such universities and TEIs are UoMacedonia, UoCrete, etc.
- No of Students is on its own.

Looking globally at the different criteria, we can better explain the different action profiles:

- NTUA has high input traffic, maximum input traffic, output traffic and maximum output traffic, and an average number of students.
- TEI Ionian Islands has low input traffic, maximum input traffic, output traffic, maximum output traffic and number of students.

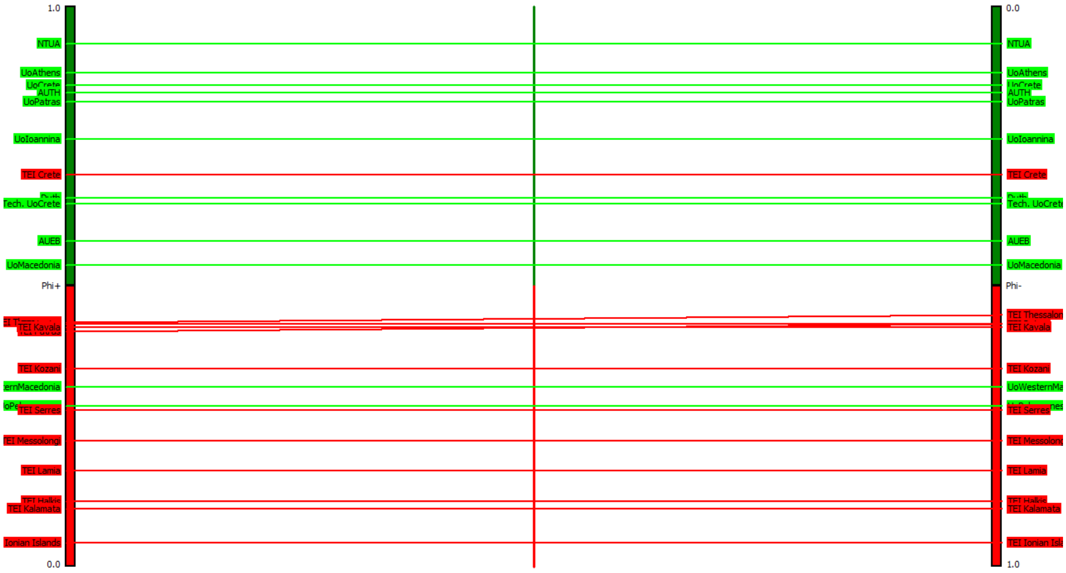

Figure 7. PROMETHEE I final rankings

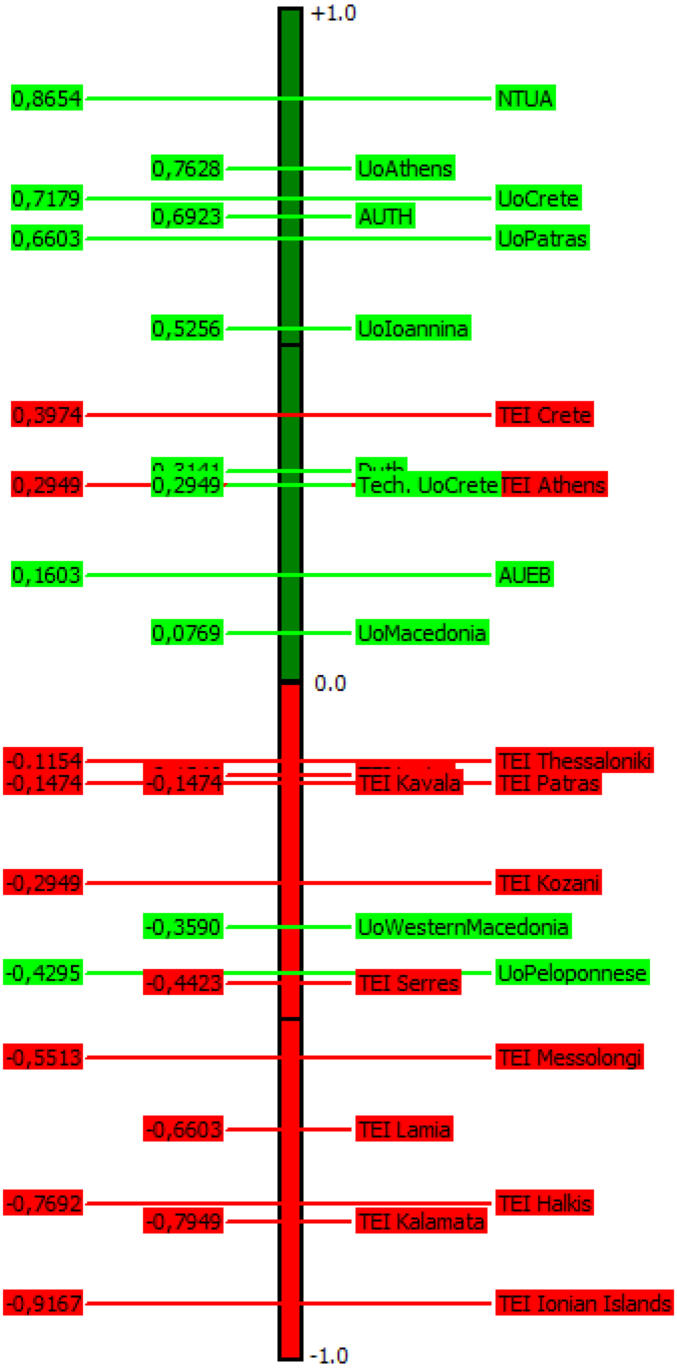

Figure 8. PROMETHEE II final rankings

Table 10. Rank using PROMETHEE

UNIVERSITY/TEI	No.	DMU	Score	Rank
NTUA	1	A	0.63	1
UoAthens	2	B	0.57	2
AUTH	3	C	0.20	4
AUEB	4	D	0.40	11
UoPatras	5	E	0.20	5
UoCrete	6	F	0.58	3
UoIoannina	7	G	0.65	6
DUTh	8	H	0.50	8
UoPeloponnese	9	I	0.84	19
UoMacedonia	10	J	0.56	12
UoWesternMacedonia	11	K	0.38	18

Tech. UoCrete	12	L	0.70	10
TEI Athens	13	M	0.10	9
TEI Patras	14	N	0.60	15
TEI Larisa	15	O	0.69	14
TEI Lamia	16	P	0.53	22
TEI Halkis	17	Q	0.15	23
TEI Kalamata	18	R	0.64	24
TEI Serres	19	S	0.54	20
TEI Thessaloniki	20	T	0.14	13
TEI Kozani	21	U	0.56	17
TEI Ionian Islands	22	V	0.77	25
TEI Messolongi	23	W	0.50	21
TEI Crete	24	Y	0.33	7
TEI Kavala	25	Z	0.59	16

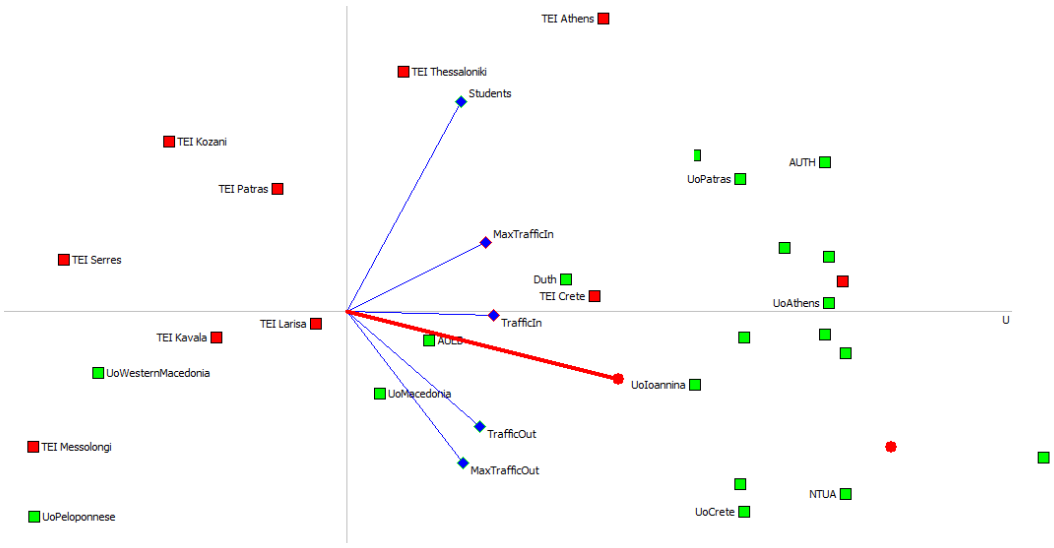

Figure 9. GAIA plane

5. Conclusions

In this paper, we have presented and compared parametric, non-parametric and mutlicriteria techniques for measuring computer networks' efficiency. The suggested approach is to treat networks as economic systems, whose efficiency should be maximized. This approach has the advantage that it can be applied even in circumstances that we do not have a complete view of the examined networks, i.e., the topology and internal traffic characteristics.

We applied DEA, SFA, and PROMETHEE in the GRNet group of interconnected networks. The rank of the DMUs that we extracted from DEA and SFA is almost the same, from which we conclude that these techniques can be used for measuring network efficiency. Moreover, we applied three different DEA models: i) CCR DEA, ii) SYS-DEA, and iii) super-efficiency DEA model. All these models can provide various levels of information to the network manager, so that a complete picture of the network can be acquired. Finally, the decision maker can adjust the weights of the criteria in PROMETHEE in order to build different scenarios. PROMETHEE results offer a number of suggestions to the network manager in order to improve the performance of the network.

The proposed study offers important managerial implications. First, network managers can gain useful information about their network by understanding exactly which items, and to what extent, need to be improved to achieve operational efficiency. Moreover, network managers can build different scenarios and experiment with different alternatives for improving their network.

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