ANALYZING EFFICIENCIES AND TOTAL FACTOR PRODUCTIVITIES OF STAR ALLIANCE MEMBER AIRLINES

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Abstract: Comparing the efficiency levels and productivities of domestic and international airline companies is an active research area in services sector and has lots of interests in business administration field. In this study, Data Envelopment Analysis and Total Factor Productivity Analysis are used to compare the efficiencies and productivities of Star Alliance member international airline companies. Eight variables, including both inputs and outputs named as Number of Annual Passengers, Daily Departures, Number of Countries Served, Number of Airports Served, Revenue Passenger (Km), Sales Revenue ($), Number of Employees and Fleet of 26 airline companies are taken place in analysis for the years 2013 and 2014. Because of price differences in access the resources of services and goods that the companies used, the Variable Returns to Scale Method of Data Envelopment Analysis is used instead of Constant Returns to Scale Method to figure out efficiencies in years. Results show that there are differences in efficiencies and productivities of airline companies by the means of using their inputs to produce outputs while some of them are wasting their resource and some others are not.

Keywords: Airlines, Total Factor

Introduction

Efficiency in the services sectors is getting much more significant issue in global trade year by year. As one of the most and rapid growing establishments in global service sector, the domestic and international airline companies have the pioneering role as in Turkey and in the world. Airline companies which are operated singular or operated as the member of an alliance group still are in the competition in locally and globally. The growing demand to this service sector creates the difficulties and makes the expenses of operating facilities higher under the competitive stress. Therefore, yearly and continuously, the efficiencies of these companies have growing importance by investors, creditors, business partners, and the governments. It is also have great importance from the view point of the airline's management, so they can gauge their own performance and compare it against other airline companies. Operated domestic or/and international, it is the responsibility of every organization to allocate, monitor and evaluate their annual expenditure and service delivery.

For this reason, in this study, Data Envelopment Analysis (DEA) and Total Factor Productivity Index (TFPI) are the generating mechanisms for efficiency scores and methodology for seeking sources of inefficiency of each and following operating year. Numerous studies have adopted DEA technique in the field of airline operations, mainly focusing on airline management and airport operation (Chiou and Chen, 2006). The main reason to select DEA technique is that it is easily applicable in many situations where the inputs and outputs cannot be converted to a common scale, as is the case here (Barros and Peypoch, 2009). And as a computational detail, the Variable Returns to Scale (VRS) Method of Data Envelopment Analysis is used instead of Constant Returns to Scale (CRS) Method to figure out efficiencies in years, because of price differences in access the resources of services and goods that the companies used. This study aims to identify the inputs which are used inefficient by the inefficient airlines and to advice them how to be efficient by adopting the scales of efficient airlines. The structure of the study is organized as follows: Airline Industry as an Alliance, Literature Survey, Data Envelopment Analysis for Efficiency Measurement, Theoretical Model, Data and Results, Conclusion and References.

The Study

Airline Industry as an Alliance: Domestic and International passenger airlines are a critical mode of transportation and play an important role in modern society. As an alliance within the concept of airline industry, the Star Alliance network is the leading global airline network, with the highest number of member airlines, daily flights, destinations and countries flown to. It was established in 1997 as the first truly global airline alliance to offer customers convenient worldwide reach and a smoother travel experience. In 1997, a group of five world-class airlines united to create something never seen before - an alliance that brings together networks, lounge access, check-in services, ticketing and dozens of other services to improve the travel experience for customers, wherever they are in the world. Star Alliance Services GmbH was created to manage the Star Alliance network on behalf of its members. It was the first alliance in the world to create this type of organization. The team is based in Frankfurt, Germany and is made up of around 70 employees from over 20 different countries. Having the mission of “Executing leadership in managing a portfolio of alliance products and services using an agreed process” Star Alliance member airlines fly to more destinations than any other airline alliance in the world – which means easier travel and quicker connections. The main goal has always been to make your travel experience smoother. To achieve this, Star Alliance member airlines are located closer together in airports and connections teams are installed for faster transfers. Common airport facilities, coordinating schedules and a range of new technologies are also frequently introduced.

The member airlines of the Star Alliance network are among the most respected in the world. In order to become members, all airlines must comply with the highest industry standards of customer service, security and technical infrastructure. Together, they offer convenient and comfortable travel to almost any destination in the world. Its acceptance by the market has been recognized by numerous awards, including the Air Transport World Market Leadership Award and Best Airline Alliance by both Business Traveller Magazine and Skytrax. The member airlines are: Adria Airways, Aegean Airlines, Air Canada, Air China, Air India, Air New Zealand, ANA, Asiana Airlines, Austrian, Avianca, Avianca in Brazil, Brussels Airlines, Copa Airlines, Croatia Airlines, EGYPTAIR, Ethiopian Airlines, EVA Air, LOT Polish Airlines, Lufthansa, Scandinavian Airlines, Shenzhen Airlines, Singapore Airlines, South African Airways, SWISS, TAP Portugal, Turkish Airlines, THAI and United (http://www.staralliance.com/en/about/organisation).

Table-1: Some Statistical Figures of Star Alliance as Combined by the End of 2014

Total revenue	179.05 BUSD		Revenue Passenger Km	1,364.83 bn
Daily departures	More than 18.500		Annual Passengers	641.10 m
Countries served	192		Number of employees	432,603
Airports served	1330		Fleet (Number of Aircraft)	4,657
Lounges	More than 1000			

Source: http://www.staralliance.com/en/about/member_airlines/

Literature Survey Related with the Airline Industry Efficiencies: Up to now, many studies on Airline Industry have been conducted and published with academic purposes. Some most recent of them published by the year 2010 are listed as given chronological order including author, number of Decision Making Units (DMU’s), study periods, methodology used, remarks and focuses: Hong and Zhang (2010): 29 international airlines, 1998-02, Standard DEA, Airlines with high share of cargo business are significantly more efficient. Merkert and Hensher (2011): 58 international airlines, 2007-09, Standard DEA and Bootstrapped Tobit Regression, Size of airlines and fleet mix decisions have an impact on technical efficiency. Zhu (2011): 21 US airlines, 2007-08, Two-stage network DEA Multi-stage network DEA models provide deeper insight into functioning of an airline. Assaf and Josiassen (2012): 31 European and US airlines, 2001-08, Bayesian Distance Frontier Model, European airlines have slightly higher efficiency and productivity growth than US airlines. Barros and Couto (2013): 23 European airlines, 2000-11, Luenberger Productivity Index and Malmquist Productivity Index, Managerial causes of technical efficiency may be due to variations in the strategies adopted by the different airlines. Barros et al. (2013): 10 US airlines, 1998-10, B-convex Model, Efficiency can be influenced by the size of the airline, mergers, and acquisitions. Choi et al. (2013): 12 US airlines, 2008-11, Service quality-adjusted DEA and Mann-Whitney test, SQ-DEA places a greater emphasis on service quality as a factor that relates to service productivity. Airlines can overcome the tradeoff between quality and productivity. Arjomandi and Seufert (2014): 48 international airlines, 2007-10, Bootstrapped DEA, Low-cost carriers are operating under increasing returns to scale. Tavassoli et al. (2014): 11 Middle Eastern airlines, 2010, Slacks-Based Measure (SBM), network DEA Deals with shared inputs and outputs with selected weights. Wu and Liao (2014): 38 international airlines, 2010, Standard DEA and Balance Score Card (BSC), Leading and lagging factors of BSC were adapted to the evaluation of operational performance of airlines along with DEA. Chang et al. (2014): 27 international airlines, 2010, Slacks-Based Measure (SBM), DEA Trade-offs between labor and capital measures poses a challenge. Fuel consumption and revenue structure are major causes of inefficient airlines. Lee and Worthington (2014): 42 US and European airlines, 2001-05, Bootstrapped DEA and Bootstrapped Truncated Regression, DEA scores are estimated simultaneously with a bootstrapped truncated regression model to explain efficiency drivers. Large airlines need to significantly reorganize and rescale their operations to remain competitive. Lu et al. (2014): 30 US airlines, 2010, Two-stage network DEA, Two-stage network model examines production and marketing efficiencies.

Data Envelopment Analysis for Efficiency Measurement: The technique, which is referred to as DEA, is able to compare the efficiency of multiple service units that provide similar services by considering their use of multiple inputs and to produce multiple outputs (Bosetti, Cassinelli & Lanza, 2003). Besides being more comprehensive and reliable than a set of operating ratios or profit measures, the DEA measure has the ability to incorporate multiple inputs and multiple outputs into both the numerator and denominator of the efficiency ratio without the need for converting to a common scale basis (Fitzsimmons & Fitzsimmons, 1998).

DEA is a linear programming model that attempts to maximize a service unit's efficiency with the performance of a group of similar service units that are delivering the same service. In the process, some units achieve 100% efficiency and are referred to as the relatively efficient units, whereas other units with efficiency scores of less than 100% are referred to as inefficient ones (Norman & Stoker, 1991). Efficiency is defined as the ratio of weighted sum of outputs to weighted sum of inputs in the model and components of this model can be explained as follows (Metters, Frei & Vargas, 1999):

Efficiency = Weighted Sum of Outputs / Weighted Sum of Inputs

Efficiency of Unit (j) = $(u_1.y_{1j} + u_2.y_{2j} + \ldots) / (v_1.x_1j + v_2.x_2j + \ldots)$

Variables in equation indicate;

u_1 = weight of output i
y_{1j} = quantity of output-1 derived from unit j
v_1 = weight of input j
x_{1j} = quantity of input-1 used by unit j

An efficiency model simplified as the above equation can be solved as a Linear Program by means of the following maximization approach (Yolalan, 1993).

$$\text{Max } h_k = \sum_{r=1}^{s} u_{rk}.Y_{rk}$$

Subject to;

$$\sum_{r=1}^{s} u_{rk}.Y_{rj} - \sum_{i=1}^{m} v_{ik}.X_{ij} \leq 0;$$

for k and j = 1,2,..., n Decision Making Units

$$\sum_{i=1}^{m} v_{ik}.X_{ik} = 1$$ Weighted Sum of Inputs Set to Unity

$U_{rk} \geq 0$; r = 1, 2, ..., s Outputs
$V_{ik} \geq 0$; i = 1, 2, ..., m Inputs

DEA evaluates the relative efficiency of organizational units, called decision making units (DMUs), with multiple inputs and outputs (Charnes et al., 1978). DEA is a linear programming based non-parametric methodology and treats each DMU as a black box, focusing entirely on the DMU's inputs, outputs, and its relative efficiency. Each DMU converts a specific level of each input into a specific level of output under appropriate assumptions. The two main DEA model assumptions are model orientation and returns-to-scale (Charnes et al., 1994; Cook et al., 2014). DEA models commonly are either input or output oriented (Cook et al., 2014) and input oriented models seek to reduce inputs while the output oriented models seek to increase outputs (Sarkis, 2007). To achieve high operational efficiency of domestic and international airlines, the airline managers must seek to reduce inputs and increase outputs simultaneously (Forsyth et al., 1986; Hirst, 2008).

Variable Returns to Scale Assumption: In economics, returns to scale and economies of scale are related but different terms that describe what happens as the scale of production increases in the long run, when all input levels including physical capital usage are variable (chosen by the firm). The term returns to scale arises in the context of a firm's production function. It explains the behavior of the rate of increase in output (production) relative to the associated increase in the inputs (the factors of production) in the long run. In the long run all factors of production are variable and subject to change due to a given increase in size (scale). While economies of scale show the effect of an increased output level on unit costs, returns to scale focus only on the relation between input and output quantities. The laws of returns to scale are a set of three interrelated and sequential laws: Law of Increasing Returns to Scale, Law of Constant Returns to Scale, and Law of Diminishing returns to Scale. If output increases by that same proportional change as all inputs change then there are constant returns to scale (CRS). If output increases by less than that proportional change in inputs, there are decreasing returns to scale (DRS). If output increases by more than that proportional change in inputs, there are increasing returns to scale (IRS). A firm's production function could exhibit different types of returns to scale in different ranges of output. Typically, there could be increasing returns at relatively low output levels, decreasing returns at relatively high output levels, and constant returns at one output level between those ranges (Zelenyuk, 2014). In mainstream microeconomics, the returns to scale faced by a firm are purely technologically imposed and are not influenced by economic decisions or by market conditions (i.e., conclusions about returns to scale are derived from the specific mathematical structure of the production function in isolation) (Gelles, Gregory M.; Mitchell, Douglas W., 1996).

Total Factor Productivity Index: In economics, total-factor productivity (TFP), also called multi-factor productivity, is a variable which accounts for effects in total output not caused by traditionally measured inputs of labor and capital. If all inputs are accounted for, then TFP can be taken as a measure of an economy's long-term technological change or technological dynamism. TFP cannot be measured directly. Instead it is a residual, often called the Solow residual, which accounts for effects in total output not caused by inputs. The equation below (in Cobb–Douglas form) represents total output (Y) as a function of total-factor productivity (A), capital input (K), labor input (L), and the two inputs' respective shares of output (**α** and **β** are the capital input share of contribution for K and L respectively). An increase in either A, K or L will lead to an increase in output. While capital and labor input are tangible, TFP appears to be more intangible as it can range from technology to knowledge of worker (human capital).

$$Y = A \times K^{\alpha} \times L^{\beta}$$

Technology growth and efficiency are regarded as two of the biggest sub-sections of Total Factor Productivity, the former possessing "special" inherent features such as positive externalities and non-rivalness which enhance its position as a driver of economic growth. Total Factor Productivity is often seen as the real driver of growth within an economy and studies reveal that whilst labor and investment are important contributors, Total Factor Productivity may account for up to 60% of growth within economies. TFP is more accurately measured in long term, since TFP can vary substantially from one year to another. It has been shown that there is a historical correlation between TFP and energy conversion efficiency (Machek, 2012).

Theoretical Model: The theoretical model of this study aims to seek the sources of inefficiency by analyzing the efficiency measurements and total factor productivity scores for each Star Alliance member airline year by year and within the upcoming time periods. The airline efficiency model consists of from four input and four output variables. Table 2 depicts the airline operating efficiency model by its input and output variables including 26 airline companies within the body of Star Alliance. The input variables used in this study are the capital assets of an airline company. By using them an airline company wants to increase the number and the value of its outputs.

Table 2: Input and Output Variables for Efficiency Evaluation of Airline Companies

Inputs (Xi)	Outputs (Yj)
X1: Fleet (Number of Aircrafts)	**Y1**: Number of Annual Passengers (x 1.000)
X2: Number of Employees	**Y2**: Daily Departures
X3: Number of Airports Served	**Y3**: Revenue Passenger (Miles)* (x 1.000.000)
X4: Number of Countries Served	**Y4**: Sales Revenue ($) (x 1.000.000)

***Revenue Passenger Miles**: RPM are measures of traffic for an airline flight, bus or train calculated by multiplying the number of revenue-paying passengers aboard the vehicle by the distance traveled. RPM can be considered the basic amount of "production" that an airline creates. In other words, RPM are defined as a summation of the products of available seat miles (ASM) between two destinations and the number of revenue passengers served on that trip. RPM represent the service demand of an airline. ASM and RPM are perishable quantities, meaning that they are nonstorable and must be used instantaneously. ASM and RPM are the two vital indicators that measure the relevant operational performance of an airline.

Methodology and Data: In this study, Data Envelopment Analysis (DEA) is used as the analysis technique for a number of reasons, including the fact that; there is no restriction on the types of variables which can be included in the analysis. In DEA studies, variables can be measured in different units and there is no need to convert them into a common scale, as is the case here. The proposed model has parameters with different units of measurement such as USA Dollar, Revenue Passenger Miles, number of aircrafts and number of passengers, etc. In this study, we also applied the VRS assumption instead of CRS while there are no fixed or standardized market prices for some of these quantities.
The data for this study was obtained from the Star Alliance web site for the years 2013 and 2014 including the 26 of 28 airline companies which's data were available for both years. In this organization the member airline companies update their basic data twice a year.

Findings

The determination of each airline company's efficiency for year 2013 and for 2014 is done by applying input oriented and Variable Returns to Scale DEA model separately. The inputs and outputs values and technical efficiency scores are showed in Table 3 as a whole. Sectoral slacks are and annual efficiency means are also given at the bottom line of the related table. The brand names of Decision Making Units (DMU's) are named as given below;

DMU01: Adria Airways
DMU02: Aegean Airlines
DMU03: Air Canada
DMU04: Air China
DMU05: Air New Zealand
DMU06: All Nippon Airways-ANA
DMU07: Asiana Airlines
DMU08: Austrian
DMU09: Avianca
DMU10: Brussels Airlines
DMU11: Copa Airlines
DMU12: Croatia Airlines
DMU13: EGYPTAIR
DMU14: Ethiopian Airlines
DMU15: EVA Air
DMU16: LOT Polish Airlines
DMU17: Lufthansa
DMU18: Scandinavian Airlines
DMU19: Shenzhen Airlines
DMU20: Singapore Airlines
DMU21: South African Airways
DMU22: SWISS
DMU23: TAP Portugal
DMU24: THAI
DMU25: Turkish Airlines-THY
DMU26: United

As it is seen from Table-3, which also contains input and output variables used in the analysis, 14 airline companies out of 26 were found technically efficient in years 2013 and 2014, respectively. Together with this, only 12 airline companies out of 14 efficient ones were found technically efficient in both years. This means %85 of them kept their relative efficiency for both years. Related with this, the average efficiency scores for these years are 0,919 and 0,910, respectively by showing a slight decrease from year 2013 to year 2014. According to the efficiency score means, the Star Alliance Group has % 9 inefficiency while it can be gained with a proper operational management.

Another question can be asked as; "Which airline company is more successful among all?" The answer is not clear at first but, when the results are evaluated together, the airline companies which are found efficient in both years and which's TFP index scores over 1,000 can be sorted out as the successful ones. Only three airline companies with names "All Nippon Airways-ANA", "Singapore Airlines" and "Turkish Airlines-THY" provide above-mentioned conditions. And, we need to look out their peer counts to find out the most successful one among best three. As a final decision, Singapore Airlines was chosen as the number one airline company by its operational capability, because it has more total peer counts (19) than All Nippon Airways-ANA (12) and Turkish Airlines-THY (1). Ethiopian Airlines has the worst technical efficiency scores (0,449 and 0,467 for the years 2013 and 2014, respectively) among all despite its TFP index is shown 1,161.

All in all, the airline managers can use the reference values of efficient airline companies as given the outputs of the DEA analysis to reduce their input values while keeping the volume and quantity of their output values in order to be efficient as the peer one(s). To do that, they also have to understand the policies and operating capabilities of the efficient ones. It is also mentioned that the airlines which operate in areas where the population is dense and world trade has main attraction could be the potential successful airlines in the future.

Table 3: Data and Analysis Results of Star Alliance Member Airline Companies for the years 2013 and 2014

Airline	Year	Y1 (1.000)	Y2	Y3 (1.000.000)	Y4 (1.000.000)	X1	X2	X3	X4	TE (VRS)	Peer Counts	TFP (Index)
Adria Airways	2013	1160	54	1220	228	13	400	18	17	1,000	5	0.986
	2014	1030	54	1060	181	10	405	18	16	1,000	6	
Aegean Airlines	2013	6100	195	6990	849	30	1347	75	21	1,000	7	0.967
	2014	6900	210	7810	849	36	1357	120	33	1,000	5	
Air Canada	2013	35000	1530	89600	12100	351	27000	179	45	0,960	0	0.963
	2014	35800	1500	88500	11900	364	27000	186	48	0,917	0	
Air China	2013	48680	900	95230	16030	301	25269	145	29	1,000	1	1.023
	2014	51010	900	103060	16090	316	25830	154	31	0,995	0	
Air New Zealand	2013	13300	574	27000	3900	103	11000	54	16	1,000	5	0.930
	2014	13700	523	28080	3700	104	11000	51	16	1,000	0	
All Nippon Airways-ANA	**2013**	**45000**	**1000**	**62500**	**15800**	**232**	**33000**	**78**	**14**	**1,000**	**3**	**1.258**
	2014	**46000**	**950**	**65530**	**16000**	**241**	**14000**	**87**	**16**	**1,000**	**9**	
Asiana Airlines	2013	15000	260	31200	5080	79	10381	71	23	0,972	0	1.061
	2014	17000	260	32800	5720	84	10183	75	24	1,000	2	
Austrian	2013	11500	400	17950	2690	77	6236	130	57	0,888	0	0.901
	2014	11300	370	17710	2069	80	6108	130	56	0,808	0	
Avianca	2013	23100	568	29100	4300	143	15400	85	18	0,866	0	0.992
	2014	24600	710	31200	4600	165	19000	100	26	0,862	0	
Brussels Airlines	2013	6000	240	5370	1310	43	3500	70	40	0,891	0	0.969
	2014	6000	240	9770	1440	45	3500	78	39	0,889	0	
Copa Airlines	2013	7140	327	20100	2250	86	8240	65	29	0,732	0	0.942
	2014	11600	333	25300	2600	98	9484	69	30	0,676	0	
Croatia Airlines	2013	1950	80	1440	303	12	1071	25	16	1,000	6	0.983
	2014	1800	80	1320	288	12	973	32	18	1,000	5	
EGYPTAIR	2013	8300	250	17600	2000	81	8000	80	64	0,576	0	0.923
	2014	8400	128	17760	1800	81	9000	78	52	0,553	0	
Ethiopian Airlines	2013	4600	63	13200	1900	58	6557	85	52	0,449	0	1.161
	2014	6000	190	21300	2400	77	8066	89	63	0,467	0	
EVA Air	2013	7500	104	26000	2200	61	6292	63	18	0,910	0	1.009
	2014	8902	137	28000	2598	67	7815	65	18	0,929	0	
LOT Polish Airlines	2013	5000	240	7290	1010	37	1700	52	34	1,000	7	0.959
	2014	5000	210	7290	1010	35	1700	46	32	1,000	3	
Lufthansa	2013	74740	1886	149780	22630	360	40622	218	82	1,000	9	0.957
	2014	76300	2086	149780	17260	430	40622	235	78	1,000	2	
Scandinavian Airlines	2013	25500	781	27800	5750	156	14100	101	34	0,995	0	1.056
	2014	27100	785	30700	5940	142	12548	123	34	1,000	6	
Shenzhen Airlines	2013	18300	475	26400	3000	104	10052	67	3	1,000	4	0.844
	2014	21350	620	31770	3210	141	13660	67	5	1,000	3	
Singapore Airlines	**2013**	**18200**	**220**	**93760**	**11930**	**102**	**14156**	**62**	**34**	**1,000**	**7**	**1.064**
	2014	**18200**	**621**	**95060**	**9200**	**105**	**14628**	**60**	**33**	**1,000**	**12**	
South African Airways	2013	6500	150	21500	3000	51	10868	42	30	0,781	0	1.041
	2014	7000	165	23100	3000	52	9273	39	27	0,809	0	
SWISS	2013	15800	420	33500	5180	92	8067	74	38	1,000	0	0.995
	2014	15970	400	35100	5170	90	8250	84	40	0,943	0	
TAP Portugal	2013	10170	320	25960	3190	71	7055	77	34	0,867	0	1.010
	2014	10700	350	28150	3070	77	6889	88	38	0,799	0	
THAI	2013	20620	270	60680	6940	95	25412	76	34	1,000	2	0.970
	2014	21510	284	63480	6420	101	25323	79	34	1,000	1	
Turkish Airlines-THY	**2013**	**39050**	**845**	**74400**	**7980**	**233**	**15857**	**245**	**105**	**1,000**	**0**	**1.048**
	2014	**46160**	**1168**	**89960**	**9560**	**260**	**19658**	**264**	**108**	**1,000**	**1**	
United	2013	140000	5300	331000	37200	1265	88000	368	62	1,000	3	1.000
	2014	140000	5100	330000	38300	1265	85000	374	59	1,000	2	

Conclusions

The main objective of this study is to demonstrate the relative operating efficiencies of the Star Alliance group member airlines using their panel data for the years 2013 and 2014. This study also investigates whether there is a difference between consecutive years. We achieved that by applying the DEA method with its Variable Returns the Scale (VRS) assumption and Malmquist Total Factor Productivity Index (TFPI) to reveal these things mentioned. By doing that, this research intends to figure out the relative efficiency conditions of member airline companies in a competitive business environment.

The main constraint of this study is that the data issued by the companies asynchronously. Therefore, the results should be examined carefully by the operational managers and policy makers. It is also advised that the derived results should not be used immediately at the tactical levels by the management of the inefficient airline companies. Due to the panel data used in this study is limited to 2 years; it is advised to use a broader time period for a reliable study outcome for the further studies on this area.

Finally, airline companies which carry more passengers, depart more (frequent) and have more RPK, while they use aircrafts with more passenger capacity, employ fewer staff, own fewer aircraft and serve fewer number of countries are the potential candidates for efficiency.

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