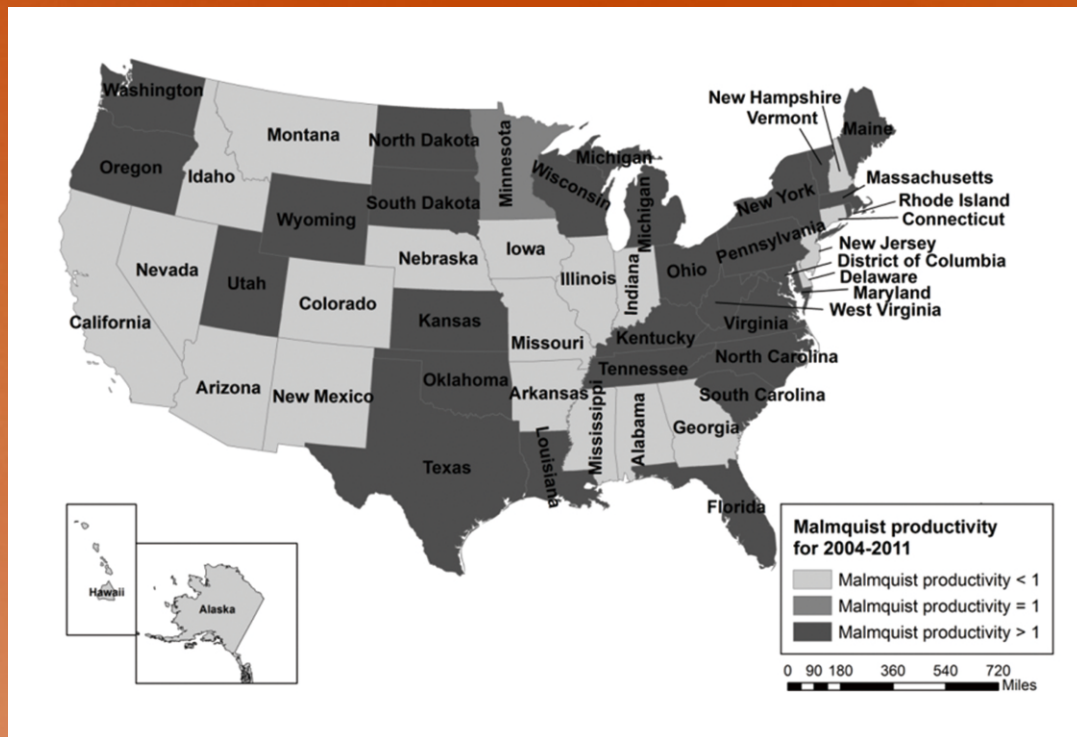


American Journal of Operations Research



ISSN: 2160-8830



Journal Editorial Board

ISSN 2160-8830 (Print) ISSN 2160-8849 (Online)

<http://www.scirp.org/journal/ajor>

Editor in Chief

Prof. Jinfeng Yue

Middle Tennessee State University, USA

Editorial Advisory Board

Prof. Bintong Chen

Prof. Wade D. Cook

Prof. Shu-Cherng Fang

Prof. Panos Kouvelis

Prof. Lawrence M. Seiford

Prof. Suresh P. Sethi

University of Delaware, USA

York University, Canada

North Carolina State University, USA

Washington University in St. Louis, USA

University of Michigan, USA

University of Texas at Dallas, USA

Editorial Board

Dr. Javier De Andrés

Prof. Janine E. Aronson

Dr. Annamaria Barbagallo

Dr. Nabil Belacel

Prof. Ignacio Castillo

Prof. Xu Chen

Prof. Muhammad El-Taha

Dr. Carmen Galé

Prof. Xianghua Gan

Prof. Xiuli He

Prof. Mhand Hifi

Prof. Zhimin Huang

Prof. Zhibin Jiang

Dr. Ricardo Josa-Fombellida

Prof. Dennis Leech

Prof. Deng-Feng Li

Prof. Liang Liang

Dr. Pedro Lorca

Prof. Charles L. Munson

Dr. Jamal Ouenniche

Prof. Joaquín Antonio Pacheco Bonrostr

Prof. Javier Ramirez Rodriguez

Prof. Bhaba R. Sarker

Prof. Renduchintala Raghavendra Kumar Sharma

Dr. Chunming (Victor) Shi

Prof. Andranik Tangian

Prof. Etsuji Tomita

Dr. Delfim F. M. Torres

Prof. Evangelos Triantaphyllou

Dr. Manish Verma

Dr. Yu Amy Xia

Prof. Yi-Min Xie

Dr. Shenghan Xu

Dr. Jiping Yang

Dr. Shilei Yang

Prof. Peng-Yeng Yin

Dr. Xiaohang Yue

University of Oviedo, Spain

University of Georgia, USA

University of Naples "Federico II", Italy

NRC Institute for Information Technology, Canada

Wilfrid Laurier University, Canada

University of Electronic Science and Technology of China, China

University of Southern Maine, USA

University of Zaragoza, Spain

The Hong Kong Polytechnic University, China

The University of North Carolina at Charlotte, USA

University of Picardie Jules Verne, France

Adelphi University, USA

Shanghai Jiao Tong University, China

University of Valladolid, Spain

University of Warwick, UK

Fuzhou University, China

University of Science and Technology of China, China

University of Oviedo, Spain

Washington State University, USA

University of Edinburgh, UK

University of Burgos, Spain

The Metropolitan Autonomous University, Mexico

Louisiana State University, USA

IIT Kanpur, India

Wilfrid Laurier University, Canada

Karlsruhe Institute of Technology, Germany

The University of Electro-Communications, Japan

University of Aveiro, Portugal

Louisiana State University, USA

McMaster University, Canada

Northeastern University, USA

RMIT University, Australia

University of Idaho, USA

Beihang University, China

Southwestern University of Finance and Economics, China

National Chi Nan University, Chinese Taipei

University of Wisconsin-Milwaukee, USA

Guest Reviewers

Jose Humberto Ablanedo-Rosas

Lingyan Cao

Yuan-Shyi Peter Chiu

Petr Ya. Ekel

Wang-Ting Hu

Vassilis Kostoglou

Ulrike Leopold-Wildburger

Chih-Chin Liang

Pedro Lorca

Yu Lu

Fabrizio Marinelli

V.N. Maurya

Frank Meisel

Jerzy Michnik

Ahmed Nait-Sidi-Moh

Hussein Naseraldin

Alain Pietrus

Han Qiao

Andre Rossi

Zhenjun Shi

Xiang Song

Nodari Vakhania

Tao Wu

Gongxian Xu

Zixiang Xu

Takeo Yamada

Xiaoning Zhang

Table of Contents

Volume 5 Number 1

January 2015

Productivity Growth in the Transportation Industries in the United States: An Application of the DEA Malmquist Productivity Index	
J. Choi, D. C. Roberts, E. S. Lee.....	1
JIT Mixed-Model Sequencing Rules: Is There a Best One?	
P. R. McMullen.....	21
Assessing the Relative Efficiency of Health Systems in Sub-Saharan Africa Using Data Envelopment Analysis	
S. Ambapour.....	30
Evaluation Indexes of Degree of Closeness between Strategy and Project Portfolio Allocation	
L. B. Bai, S. J. Bai.....	38

American Journal of Operations Research (AJOR)

Journal Information

SUBSCRIPTIONS

The *American Journal of Operations Research* (Online at Scientific Research Publishing, www.SciRP.org) is published bimonthly by Scientific Research Publishing, Inc., USA.

Subscription rates:

Print: \$79 per issue.

To subscribe, please contact Journals Subscriptions Department, E-mail: sub@scirp.org

SERVICES

Advertisements

Advertisement Sales Department, E-mail: service@scirp.org

Reprints (minimum quantity 100 copies)

Reprints Co-ordinator, Scientific Research Publishing, Inc., USA.

E-mail: sub@scirp.org

COPYRIGHT

COPYRIGHT AND REUSE RIGHTS FOR THE FRONT MATTER OF THE JOURNAL:

Copyright © 2015 by Scientific Research Publishing Inc.

This work is licensed under the Creative Commons Attribution International License (CC BY).

<http://creativecommons.org/licenses/by/4.0/>

COPYRIGHT FOR INDIVIDUAL PAPERS OF THE JOURNAL:

Copyright © 2015 by author(s) and Scientific Research Publishing Inc.

REUSE RIGHTS FOR INDIVIDUAL PAPERS:

Note: At SCIRP authors can choose between CC BY and CC BY-NC. Please consult each paper for its reuse rights.

DISCLAIMER OF LIABILITY

Statements and opinions expressed in the articles and communications are those of the individual contributors and not the statements and opinion of Scientific Research Publishing, Inc. We assume no responsibility or liability for any damage or injury to persons or property arising out of the use of any materials, instructions, methods or ideas contained herein. We expressly disclaim any implied warranties of merchantability or fitness for a particular purpose. If expert assistance is required, the services of a competent professional person should be sought.

PRODUCTION INFORMATION

For manuscripts that have been accepted for publication, please contact:

E-mail: ajor@scirp.org

Productivity Growth in the Transportation Industries in the United States: An Application of the DEA Malmquist Productivity Index

Jaesung Choi^{1*}, David C. Roberts², EunSu Lee³

¹Transportation and Logistics Program, North Dakota State University, Fargo, ND, USA

²Department of Agribusiness & Applied Economics, North Dakota State University, Fargo, ND, USA

³Upper Great Plains Transportation Institute, North Dakota State University, Fargo, ND, USA

Email: *jaesung.choi@ndsu.edu, David.C.Roberts@ndsu.edu, eunsu.lee@ndsu.edu

Received 21 October 2014; revised 20 November 2014; accepted 12 December 2014

Copyright © 2015 by authors and Scientific Research Publishing Inc.

This work is licensed under the Creative Commons Attribution International License (CC BY).

<http://creativecommons.org/licenses/by/4.0/>



Open Access

Abstract

This study reviews productivity growth in the five major transportation industries in the United States (airline, truck, rail, pipeline, and water) and the pooled transportation industry from 2004 to 2011. We measure the average productivity for these eight years by state in each transportation industry and the annual average productivity by transportation industry. The major findings are that the U.S. transportation industry shows strong and positive productivity growth except that in the years of the global financial crisis in 2007, 2008, and 2010, and among the five transportation industries, the rail and water sectors show the highest productivity growth in 2011.

Keywords

DEA Malmquist Productivity Index, Productivity Growth, U.S. Transportation Industry

1. Introduction

Transportation is an important part of development and growth in economic activities. When a transportation industry is efficient, it can provide more economic and social benefits to residents, businesses, and the government through the decrease of congestion, just-in-time business work, and environmental pollution caused by an inefficient transportation mode. When a transportation industry is deficient, however, it leads to unexpected op-

*Corresponding author.

portunity costs or lost business opportunities. In many developed countries, the proportion of transportation to Gross Domestic Product (GDP) ranges from 6% to 12% [1]. The transportation industry in the United States has long had a major effect on growth at the city, region, and state levels.

The U.S. transportation industry is one of the largest in the world. The U.S. Department of Transportation explains in its freight shipments report that the transportation industry brings together more than seven million domestic businesses and 288 million citizens with the employment of one out of seven U.S. workers. It is noted that “more than \$1 out of every \$10 produced in the U.S. GDP is related to transportation activity” [2].

The increase in productivity in an industry occurs when growth in output is proportionately greater than growth in inputs. In the transportation industry, the measure of productivity growth has been an important issue for both transportation economists and transportation policymakers for centuries. A number of attempts have been made to solve this issue, with Data Envelopment Analysis (DEA) popular for the analysis of productivity gains. DEA has three main advantages: 1) The number of empirical applications is very large; 2) It does not place any restrictions on the assumption of the inefficiency term and technology; 3) A production relationship regarding the form of the frontier between inputs and outputs is not restricted [3]-[8].

The productivity growth of efficiency and technological change in various industries including transportation has been studied. For example, Farrell [9] measured productive efficiency based on price and technical efficiencies in U.S. agricultural production for the 48 states in 1952. The two key concepts used to measure a farmer’s success were choosing the best set of inputs and producing the maximum output from a given set of inputs, respectively. Unlike Farrell [9], Charnes *et al.* [10] provided a nonlinear programming model to define efficiency and thus evaluated the performance of nonprofit public entities. In 1982, Caves *et al.* [11] developed an index number procedure for input, output, and productivity, while Sueyoshi [12] provided an effectively designed algorithmic procedure for the measurement of technical, allocative, and overall efficiencies. These were provided as a basis to construct a Malmquist productivity index, which was later developed by Färe *et al.* [3], Färe and Grosskopf [4], and Färe *et al.* [5] [6]. In 1992, Färe *et al.* [3] [5] developed the Malmquist input-based productivity index to measure productivity growth in Swedish pharmacies and in 1994 used the Malmquist output-based productivity index to analyze productivity growth in industrialized countries and Swedish hospitals.

Following Färe and Grosskopf [4], a unified theoretical explanation of three productivity indexes (Malmquist, Fisher, and Törnqvist) was provided. In the 2000s, research started to compare the conventional Malmquist productivity index with an environmentally sensitive Malmquist productivity index in applications of the U.S. agricultural industry, the U.S. trucking industry, and 10 OECD countries [13]-[15].

Nevertheless, the conventional Malmquist productivity index has still been used to measure productivity growth. For example, Chen and Ali [16] employed it for the productivity measurement of seven computer manufacturers in the Fortune Global 500 from 1991 to 1997, while Liu and Wang [17] applied it to Taiwan’s semiconductor industry during 2000 to 2003. Recently, the high-tech industry in China and Turkish electricity distribution industry have been analyzed to measure efficiency performance by Qazi and Yulin [18] and Celen [8], respectively.

The growth of the U.S. transportation industry has been led by the five major transportation modes: truck, rail, airline, pipeline, and water. For the past ten years, their growth patterns have been more complicated in the age of limitless competition based on the needs of the times, obtainable output profits from the input resources available, and levels of technological advances in each industry. The objective of this study utilizes the conventional Malmquist productivity index to measure productivity growth in these five major transportation industries in 51 U.S. states as well as the pooled transportation industry between 2004 and 2011. The state-level findings from this study are expected to be used to evaluate whether each state’s transport policies have sufficiently functioned to enhance productivity growth at its boundary. The structure of the remainder of this paper is as follows. Section 2 explains the methodology used and Section 3 describes the data. In Section 4, the results of the empirical analysis are shown and Section 5 concludes the study.

2. Methodology

Let us define:

- x^t = Input vector from time period, $t = 1, \dots, T$.
- y^t = Output vector from time period, $t = 1, \dots, T$.
- S^t = Production technology that x^t can produce y^t .

Four output distance functions are required to calculate the output-based Malmquist productivity index, and the first distance function is defined as follows [3]-[6]:

$$D_0^t(x^t, y^t) = \inf \left\{ \theta : (x^t, y^t/\theta) \in S^t \right\} \quad (1)$$

The first distance function means the maximum change in outputs using a set of given inputs with the technology at t , and it should be less than or equal to 1 if and only if $(x^t, y^t) \in S^t$. If $D_0^t(x^t, y^t) = 1$, then it means that (x^t, y^t) is on the technology frontier.

The mixed-period hyperbolic distance function in Equation (2) evaluates the maximum change in outputs using a set of $t+1$ inputs compared with the t benchmark technology:

$$D_0^t(x^{t+1}, y^{t+1}) = \inf \left\{ \theta : (x^{t+1}, y^{t+1}/\theta) \in S^t \right\} \quad (2)$$

In Equation (3), the mixed-period distance function for the maximum change in outputs using a set of t inputs with the benchmark technology at $t+1$ is evaluated:

$$D_0^{t+1}(x^t, y^t) = \inf \left\{ \theta : (x^t, y^t/\theta) \in S^{t+1} \right\} \quad (3)$$

The fourth distance function evaluates the maximum change in outputs using a set of $t+1$ inputs compared with the $t+1$ benchmark technology:

$$D_0^{t+1}(x^{t+1}, y^{t+1}) = \inf \left\{ \theta : (x^{t+1}, y^{t+1}/\theta) \in S^{t+1} \right\} \quad (4)$$

Following Färe *et al.* [3] and Färe *et al.* [5] [6], the output-based Malmquist productivity index is defined as

$$M_0^{t+1}(x^{t+1}, y^{t+1}, x^t, y^t) = \left[\frac{D_0^t(x^{t+1}, y^{t+1}) D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t) D_0^{t+1}(x^t, y^t)} \right]^{1/2} \quad (5)$$

The equivalent index is redefined as

$$M_0^{t+1}(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)} \left[\frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^{t+1}, y^{t+1})} \frac{D_0^t(x^t, y^t)}{D_0^{t+1}(x^t, y^t)} \right]^{1/2} \quad (6)$$

The output-oriented method measures how much output quantities can proportionally increase without increasing input quantities [19]. Equation (5) is the geometric mean of two Malmquist productivity indexes, and in Equation (6), the output-based Malmquist productivity index is converted into two terms: the first term out of the square brackets indicates the efficiency change between two periods, t and $t+1$, while the geometric mean of the second term in the square brackets captures technical progress in period $t+1$ and t . If the value of the output-based Malmquist productivity index in Equation (6) is equal to one, then no productivity growth occurs between these two periods, whereas if it is more (less) than one, there is positive (negative) productivity growth between these two periods. Efficiency and technological change have the same interpretation. For example, zero means nothing happens; however, if greater (less) than one, there is positive (negative) change [3]-[6].

3. Data

The data in this study consist of three proxies for inputs and one proxy for output in the five major transportation industries in the U.S. between 2004 and 2011¹. The output-based Malmquist productivity index requires only data for inputs and output(s): input data are yearly intermediate inputs such as energy, materials, and purchased-service inputs and output data is represented by annual GDP, which is equivalent to value added. The Bureau of Economic Analysis (BEA) defines the composition of gross output by industry as the summation of intermediate inputs and value added [20]. The BEA, however, only provides to the public yearly intermediate inputs data at the national level for each industry, not by state. Therefore, the extent of taxes that each state collected in the

¹This study has some limitations due to the data. Heterogeneity caused by exogenous economic shocks—*i.e.* shocks caused by general recessions, rather than by the transportation sector. To reduce the introduction of statistical bias and/or inconsistency, data prior to the economic recovery of 2004 were eliminated. The final year of the study uses data from 2011, however, so the possibility of bias and/or inconsistency still exists.

transportation industries from 2004 to 2011 were used to estimate the best-possible approximation for intermediate inputs by state over time. This is based on the assumption that more taxes paid by a transportation industry in a state means more purchased inputs to produce output. For example, if the state of North Dakota collected \$4 billion in its air transportation industry in 2004 compared with \$10,229 billion in the U.S. airline transportation industry, then each energy, materials, and purchased-service input for the airline transportation industry in North Dakota is calculated by multiplying the proportion of $\frac{4}{10,229}$ by the national level of each intermediate input.

All data were obtained from the online database of the BEA in 2013, and they are measured in millions of dollars [21].

Table 1 shows that the values of output produced have been proportionally increasing with those of the intermediate inputs used in the airline, truck, rail, and water transportation industries from 2004 to 2011 excluding 2009, which shows a slight decrease in output values; the pipeline transportation industry has been decreasing in terms of the input values used. The value of gross output in each transportation industry is occupied in order for the truck, airline, rail, water, and pipeline transport modes. Truck transportation is the largest transportation industry in terms of GDP, almost equal to the sum of the production values of the other four industries. The truck and airline transportation industries show much more intensive usages of energy and service inputs compared with materials inputs; that might be attributed to their fundamental industry structures. The pooled transportation industry summarizes the change in the three intermediate inputs utilized: materials inputs consist of much lower amounts compared with energy and purchased-service inputs.

4. Empirical Results

The traditional Malmquist productivity indexes for each transportation industry as well as the pooled transportation industry are estimated in **Table 3** to **Table 9**, by using DEA Programming (DEAP) 2.1. First, in **Table 3** to **Table 8**, the average productivity for the eight years by state for each transportation industry is shown. Second, **Table 9** provides the annual average productivities for the transportation industries over time. In these tables, the sources of productivity growth are decomposed into an efficiency change component and a technological change component. Färe *et al.* [5] defined efficiency change as catching up, that is how much closer a state can approach the ideal frontier in a transportation industry, and technological change as an innovation, namely how much the ideal frontier shifts because of the existing technology.

In **Table 2**, the three non-parametric statistical tests such as Median test, Kruskal-Wallis test, and Van der Waerden test are tested to evaluate the validity of the Malmquist productivities in each transportation industry and the pooled transportation industry. Their null hypothesis of the six population distribution functions (airline, truck, rail, pipeline, water, and pooled transportation industries) are identical is rejected at the 1% significance level. This implies that the Malmquist productivities by state in the five major transportation industries and the pooled transportation industry show significantly different [22].

Table 3 shows the Malmquist productivity and its decomposition in the pooled model of the U.S. transportation industry from 2004 to 2011. On average, a positive productivity growth of 0.5% by state is shown, which is attributed to a 4.6% efficiency growth and a technological decline of 3.9%. This finding means that the transportation industry in a state has marginally increased growth on average, while its innovation movement is far below the efforts of catching up to the frontier. All states experience negative growth in technological change on average; therefore, if productivity growth in a state is positive, this suggests that its technological decline is offset or surpassed by an efficiency gain. Altogether, 28 states² show positive productivity growth, and of these, the Malmquist productivity changes in the following 17 states average at least 10%: New York, North Carolina, North Dakota, Ohio, Oklahoma, Oregon, South Carolina, South Dakota, Tennessee, Texas, Utah, Vermont, Virginia, Washington, West Virginia, Wisconsin, and Wyoming. **Figure 1** depicts the geographic representation of average productivity for the eight years by state in the pooled transportation industry: Malmquist productivity < 1, productivity decline; Malmquist productivity = 1, no change in productivity; Malmquist productivity > 1, productivity growth.

The productivity measurement in the U.S. transportation industry by state is now described more in detail

²28 states are as follows: Florida, Kansas, Kentucky, Louisiana, Maine, Maryland, Massachusetts, Michigan, Minnesota, New York, North Carolina, North Dakota, Ohio, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Carolina, South Dakota, Tennessee, Texas, Utah, Vermont, Virginia, Washington, West Virginia, Wisconsin, and Wyoming.

Table 1. Annual GDP (value added) and intermediate inputs in each transportation industry and the pooled transportation industry, 2004-2011 (unit: billions of dollars).

Airline transportation	2004	2005	2006	2007	2008	2009	2010	2011
GDP	56.1	55.7	59.7	60.2	59.9	59.4	66.1	69.6
Intermediate inputs	66.4	74.5	80.5	89.6	101	72.1	79.8	92.1
Energy inputs	18.1	27.1	29.6	40.1	49.6	25.6	33	41.8
Materials inputs	2.1	1.5	1.8	2.6	2.7	1.9	1.9	2.3
Purchased-service inputs	46.2	46	49.1	46.9	48.7	44.6	44.8	48
Truck transportation	2004	2005	2006	2007	2008	2009	2010	2011
GDP	110.7	119.6	125.3	127.2	122.3	114.8	119.8	126
Intermediate inputs	122	136.8	148.4	153.7	162.1	116.2	128.5	149.1
Energy inputs	30.1	41.1	46.8	50.9	60.4	35.5	35.1	50
Materials inputs	13.3	13.8	14.7	18.5	17.6	13.8	13.6	16
Purchased-service inputs	78.6	81.9	86.9	84.2	84.1	67	79.7	83.1
Rail transportation	2004	2005	2006	2007	2008	2009	2010	2011
GDP	24.3	27	30.6	31.7	35.1	31	32.2	36.7
Intermediate inputs	26.4	32	36.6	38	43.4	32.4	43.7	49.1
Energy inputs	3.5	5.7	6.8	7.7	11.2	4.9	8.4	10.8
Materials inputs	5.5	6	6.7	7.7	9.6	6.9	8.9	9.8
Purchased-service inputs	17.4	20.3	23.1	22.6	22.6	20.7	26.4	28.5
Pipeline transportation	2004	2005	2006	2007	2008	2009	2010	2011
GDP	8.3	8.9	11.7	12.8	14.3	13.9	13.8	14.5
Intermediate inputs	11.9	12.8	13.6	14.1	14.1	10.3	8.3	6.4
Energy inputs	1	1.1	1.2	1.1	1.5	0.5	0.7	0.6
Materials inputs	2.2	2.2	2.4	2.4	2.3	1.4	1.3	1
Purchased-service inputs	8.7	9.4	10.1	10.6	10.4	8.4	6.3	4.8
Water transportation	2004	2005	2006	2007	2008	2009	2010	2011
GDP	31.3	34.8	36.6	39.6	41.3	42.8	43.5	45.6
Intermediate inputs	22.4	21.7	19.2	21.6	23.3	21.5	23.3	25.4
Energy inputs	7.7	9.1	7.3	10.1	11.1	6.9	9.9	12.7
Materials inputs	1.7	1.3	1.4	1.9	1.8	1.8	1.3	1.5
Purchased-service inputs	13	11.2	10.5	9.7	10.4	12.8	12.1	11.2
Pooled transportation	2004	2005	2006	2007	2008	2009	2010	2011
GDP	230.7	246	263.9	271.5	272.9	261.9	275.4	292.4
Intermediate inputs	249.1	277.8	298.3	317	343.9	252.5	283.6	322.1
Energy inputs	60.4	84.1	91.7	109.9	133.8	73.4	87.1	115.9
Materials inputs	24.8	24.8	27	33.1	34	25.8	27	30.6
Purchased-service inputs	163.9	168.8	179.7	174	176.2	153.5	169.3	175.6

Table 2. Non-parametric statistical tests to assess the validity of the Malmquist productivities.

Statistical tests	P values
Median test	<0.0001***
Kruskal-Wallis test	<0.0001***
Van der Waerden test	<0.0001***

Notes: the null hypothesis of the three tests is that the six population distribution functions are identical; *** indicates significance at 1%.

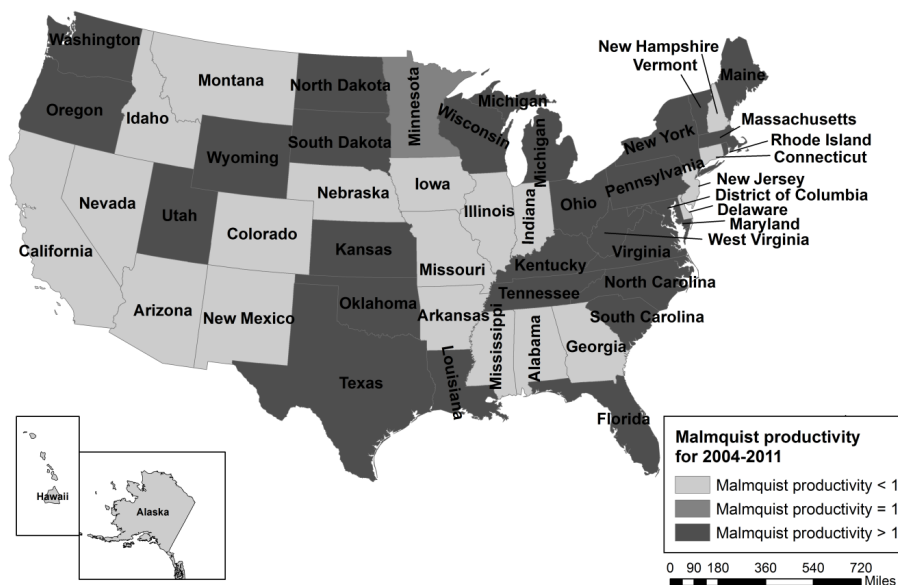


Figure 1. Geographic representation of average Malmquist productivity for 2004-2011 by state in the pooled transportation industry.

with the results of the five major transportation industries. **Table 4** shows the changes in Malmquist productivity, efficiency, and technology in the airline transportation industry between 2004 and 2011. Productivity growth by state averages close to zero due to the increase of 1% in efficiency change and the decrease of 1.1% in technological change; therefore, the airline transportation industry by state on average shows that growth itself might be stuck at zero or at worst showing a slight decline during the study period. Nevertheless, 27 of the 51 states show positive productivity growth, with Texas and Wyoming having the highest growth of 10.3%. **Figure 2** depicts the geographic representation of average productivity for 2004-2011 by state in the airline transportation industry.

Table 5 shows the Malmquist productivity and its decomposition in the truck transportation industry from 2004 to 2011. On average, a negative productivity growth of 2.2% per state is shown and this is decomposed into an efficiency gain of 0.6% and a technological decline of 2.7%. The truck industry in each state shows all negative technological changes, implying that innovation has declined over time on average; however, the productivity growth changes in the 20 states on average show non-zero growth due to the high levels of catching up. It is noted that productivity growth in Kansas, Kentucky, and Louisiana is much higher than that in the other 20 states with positive growth (19.1%, 16.7%, and 16.5%, respectively). **Figure 3** depicts the geographic representation of average productivity for 2004-2011 by state in the truck transportation industry.

In **Table 6**, the changes in Malmquist productivity, efficiency, and technology in the rail transportation industry are shown between 2004 and 2011. On average, the rail transportation industry by state shows a negative productivity growth of 1.1% based on a decrease of 5.2% in efficiency change and an increase of 4.3% in technological change. The results of the rail industry are interesting in two regards. First, the 16 states showing positive productivity growth had been growing with a high average productivity growth of 7% to 54.9%. In particular, the productivity growth rates in West Virginia, Texas, Utah, Vermont, Washington, Wyoming, and Wisconsin

Table 3. Malmquist productivity and its decomposition in the pooled model of the U.S. transportation industry, 2004-2011.

State	Efficiency change	Technological change	Productivity
Alabama	0.914	0.951	0.869
Alaska	0.927	0.959	0.889
Arizona	0.918	0.969	0.890
Arkansas	0.969	0.967	0.937
California	0.970	0.959	0.930
Colorado	0.972	0.947	0.921
Connecticut	0.914	0.967	0.884
Delaware	0.940	0.964	0.906
District of Columbia	1.013	0.975	0.988
Florida	1.052	0.972	1.022
Georgia	1.035	0.961	0.994
Hawaii	0.988	0.978	0.966
Idaho	0.964	0.972	0.937
Illinois	0.922	0.955	0.880
Indiana	0.876	0.959	0.840
Iowa	0.859	0.948	0.814
Kansas	1.119	0.956	1.070
Kentucky	1.108	0.960	1.063
Louisiana	1.102	0.958	1.056
Maine	1.101	0.966	1.064
Maryland	1.116	0.960	1.072
Massachusetts	1.084	0.954	1.034
Michigan	1.047	0.964	1.010
Minnesota	1.051	0.952	1.000
Mississippi	0.839	0.957	0.803
Missouri	0.858	0.968	0.830
Montana	0.846	0.950	0.803
Nebraska	0.984	0.964	0.949
Nevada	0.976	0.953	0.930
New Hampshire	0.968	0.961	0.931
New Jersey	0.959	0.955	0.916
New Mexico	0.961	0.941	0.905
New York	1.179	0.944	1.113
North Carolina	1.188	0.969	1.151
North Dakota	1.184	0.969	1.148

Continued

Ohio	1.177	0.963	1.134
Oklahoma	1.192	0.957	1.141
Oregon	1.159	0.950	1.101
Pennsylvania	1.114	0.960	1.069
Rhode Island	1.127	0.961	1.083
South Carolina	1.166	0.957	1.115
South Dakota	1.170	0.965	1.129
Tennessee	1.155	0.973	1.123
Texas	1.239	0.970	1.201
Utah	1.195	0.963	1.151
Vermont	1.182	0.951	1.125
Virginia	1.179	0.962	1.135
Washington	1.206	0.962	1.160
West Virginia	1.190	0.963	1.147
Wisconsin	1.165	0.971	1.131
Wyoming	1.161	0.972	1.128
Average	1.046	0.961	1.005

Table 4. Malmquist productivity and its decomposition in the airline transportation industry in the U.S., 2004-2011.

State	Efficiency change	Technological change	Productivity
Alabama	1.031	0.979	1.009
Alaska	1.013	0.995	1.008
Arizona	1.030	1.039	1.070
Arkansas	1.070	0.967	1.034
California	1.046	0.944	0.988
Colorado	0.996	1.007	1.003
Connecticut	0.934	0.991	0.925
Delaware	0.944	0.983	0.927
District of Columbia	0.941	0.979	0.922
Florida	0.908	0.995	0.903
Georgia	0.908	1.039	0.943
Hawaii	1.056	0.967	1.021
Idaho	1.005	0.944	0.950
Illinois	0.953	1.007	0.960
Indiana	0.953	0.991	0.944
Iowa	0.964	0.983	0.947

Continued

Kansas	0.999	0.979	0.978
Kentucky	0.998	0.995	0.993
Louisiana	1.013	1.039	1.052
Maine	1.112	0.967	1.075
Maryland	1.076	0.944	1.016
Massachusetts	1.000	1.007	1.007
Michigan	0.980	0.991	0.971
Minnesota	0.991	0.983	0.974
Mississippi	0.942	0.979	0.922
Missouri	0.961	0.995	0.956
Montana	0.971	1.039	1.009
Nebraska	1.026	0.967	0.992
Nevada	1.018	0.944	0.961
New Hampshire	0.952	1.007	0.959
New Jersey	0.914	0.991	0.905
New Mexico	0.928	0.983	0.912
New York	0.971	0.979	0.950
North Carolina	1.099	0.995	1.093
North Dakota	1.055	1.039	1.097
Ohio	1.133	0.967	1.095
Oklahoma	1.093	0.944	1.032
Oregon	1.023	1.007	1.030
Pennsylvania	1.014	0.991	1.005
Rhode Island	1.041	0.983	1.023
South Carolina	0.997	0.979	0.976
South Dakota	0.996	0.995	0.991
Tennessee	0.963	1.039	1.001
Texas	1.141	0.967	1.103
Utah	1.129	0.944	1.066
Vermont	1.048	1.007	1.055
Virginia	1.026	0.991	1.017
Washington	1.079	0.983	1.061
West Virginia	1.041	0.979	1.020
Wisconsin	1.045	0.995	1.040
Wyoming	1.061	1.039	1.103
Average	1.01	0.989	0.998

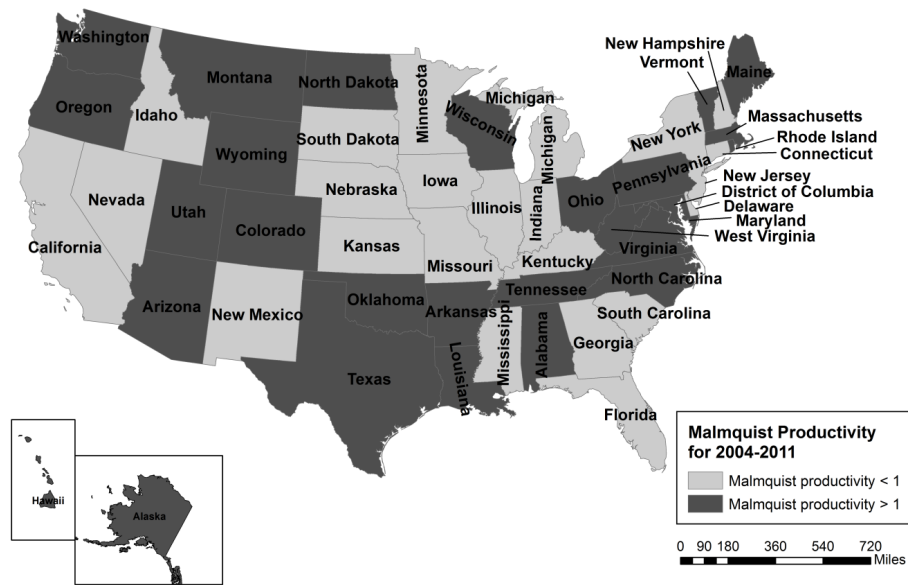


Figure 2. Geographic representation of average Malmquist productivity for 2004-2011 by state in the airline transportation industry.

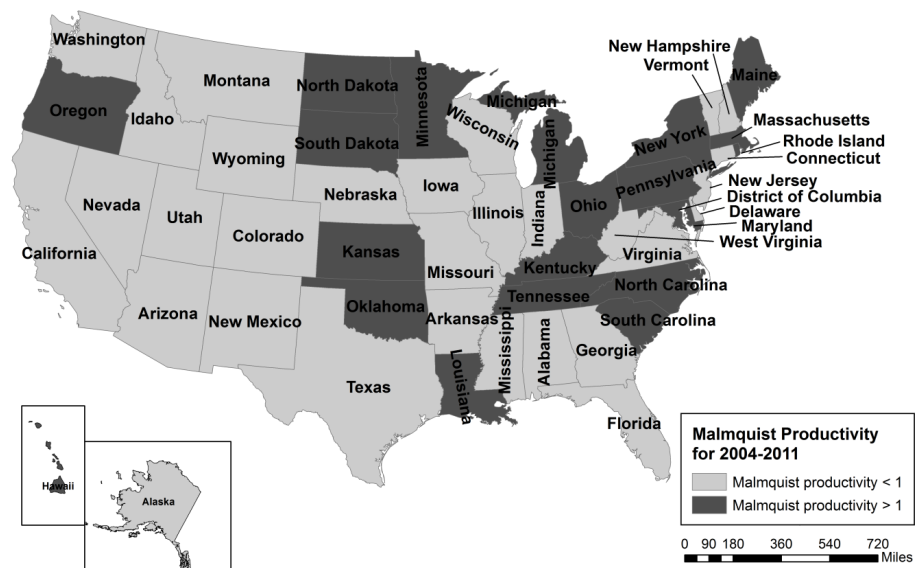


Figure 3. Geographic representation of average Malmquist productivity for 2004-2011 by state in the truck transportation industry.

reach 54.9%, 47.7%, 46.9%, 41.9%, 37.1%, 37.1%, and 36.8%, respectively. Second, all 49 states show at least 0.8% annual average innovation growth, meaning that innovation has been continuously shifting on average. **Figure 4** depicts the geographic representation of average productivity for 2004-2011 by state in the rail transportation industry.

Table 7 shows the change in Malmquist productivity and its decomposition in the pipeline transportation industry by state from 2004 to 2011. On average, the productivity decline by state in this industry is the highest of the five major transportation industries, showing -11.2% . This is explained by the severe annual average technological decline of 18.3% and the 10% increase in efficiency change. Excluding the seven states of Maryland, Massachusetts, Michigan, Minnesota, Mississippi, Missouri, and West Virginia, the productivity change in the remaining states averages much less than zero. Innovation in all states had been declining with much lower technological change, with some states even showing decreases in both efficiency and technological change:

Table 5. Malmquist productivity and its decomposition in the truck transportation industry in the U.S., 2004-2011.

State	Efficiency change	Technological change	Productivity
Alabama	0.981	0.971	0.953
Alaska	0.961	0.98	0.942
Arizona	0.964	0.975	0.939
Arkansas	0.974	0.972	0.946
California	0.956	0.977	0.934
Colorado	0.94	0.974	0.915
Connecticut	0.924	0.968	0.894
Delaware	0.955	0.965	0.921
District of Columbia	1.004	0.971	0.975
Florida	0.991	0.98	0.971
Georgia	1.008	0.975	0.983
Hawaii	1.039	0.972	1.009
Idaho	0.992	0.977	0.969
Illinois	0.97	0.974	0.944
Indiana	0.982	0.968	0.95
Iowa	0.996	0.965	0.961
Kansas	1.226	0.971	1.191
Kentucky	1.19	0.98	1.167
Louisiana	1.195	0.975	1.165
Maine	1.117	0.972	1.086
Maryland	1.116	0.977	1.09
Massachusetts	1.075	0.974	1.047
Michigan	1.103	0.968	1.068
Minnesota	1.09	0.965	1.051
Mississippi	0.843	0.971	0.819
Missouri	0.827	0.98	0.811
Montana	0.828	0.975	0.807
Nebraska	0.971	0.972	0.944
Nevada	0.962	0.977	0.94
New Hampshire	0.956	0.974	0.931
New Jersey	0.966	0.968	0.935
New Mexico	0.968	0.965	0.934
New York	1.062	0.971	1.032
North Carolina	1.084	0.98	1.063
North Dakota	1.089	0.975	1.061

Continued

Ohio	1.068	0.972	1.038
Oklahoma	1.076	0.977	1.051
Oregon	1.047	0.974	1.02
Pennsylvania	1.059	0.968	1.025
Rhode Island	1.065	0.965	1.028
South Carolina	1.049	0.971	1.019
South Dakota	1.042	0.98	1.021
Tennessee	1.038	0.975	1.011
Texas	0.947	0.972	0.92
Utah	0.942	0.977	0.92
Vermont	0.918	0.974	0.894
Virginia	0.969	0.968	0.938
Washington	0.965	0.965	0.931
West Virginia	0.992	0.971	0.964
Wisconsin	0.981	0.98	0.962
Wyoming	0.989	0.975	0.964
Average	1.006	0.973	0.978

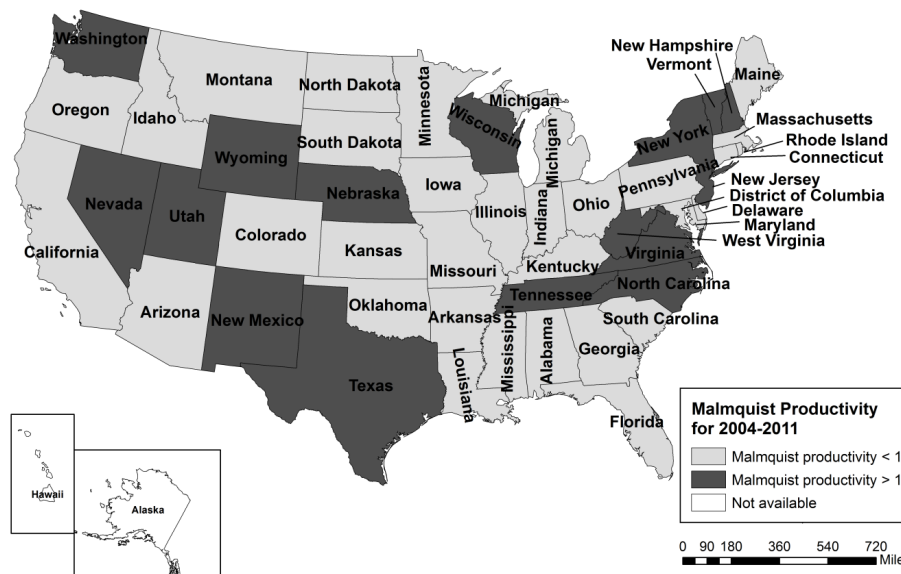


Figure 4. Geographic representation of average Malmquist productivity for 2004-2011 by state in the rail transportation industry.

Florida, Louisiana, North Dakota, Ohio, Oklahoma, Pennsylvania, South Carolina, and Tennessee. **Figure 5** depicts the geographic representation of average productivity for 2004-2011 by state in the pipeline transportation industry.

In **Table 8**, Malmquist productivity and its decomposition in the water transportation industry are shown between 2004 and 2011. Average productivity growth in the water transportation industry in each state shows close to zero growth or a slight increase. On average, productivity growth is 0.1%, which is decomposed into an

Table 6. Malmquist productivity and its decomposition in the rail transportation industry in the U.S., 2004-2011.

State	Efficiency change	Technological change	Productivity
Alabama	0.885	1.031	0.912
Arizona	0.772	1.026	0.793
Arkansas	0.762	1.072	0.817
California	0.768	1.052	0.808
Colorado	0.763	1.008	0.769
Connecticut	0.786	1.037	0.816
Delaware	0.811	1.064	0.862
District of Columbia	0.793	1.059	0.839
Florida	0.835	1.031	0.861
Georgia	0.845	1.026	0.867
Idaho	0.812	1.072	0.870
Illinois	0.823	1.052	0.865
Indiana	0.813	1.008	0.819
Iowa	0.828	1.037	0.859
Kansas	0.867	1.064	0.922
Kentucky	0.835	1.059	0.884
Louisiana	0.796	1.031	0.821
Maine	0.847	1.026	0.869
Maryland	0.843	1.072	0.904
Massachusetts	0.871	1.052	0.915
Michigan	0.844	1.008	0.851
Minnesota	0.815	1.037	0.845
Mississippi	0.836	1.064	0.889
Missouri	0.821	1.059	0.869
Montana	0.907	1.031	0.935
Nebraska	1.043	1.026	1.070
Nevada	1.023	1.072	1.097
New Hampshire	1.072	1.052	1.127
New Jersey	1.084	1.008	1.092
New Mexico	1.111	1.037	1.152
New York	1.152	1.064	1.226
North Carolina	1.076	1.059	1.139
North Dakota	0.942	1.031	0.971
Ohio	0.916	1.026	0.940
Oklahoma	0.898	1.072	0.963

Continued

Oregon	0.901	1.052	0.948
Pennsylvania	0.879	1.008	0.886
Rhode Island	0.890	1.037	0.923
South Carolina	0.903	1.064	0.961
South Dakota	0.893	1.059	0.945
Tennessee	1.161	1.031	1.197
Texas	1.439	1.026	1.477
Utah	1.370	1.072	1.469
Vermont	1.349	1.052	1.419
Virginia	1.279	1.008	1.289
Washington	1.322	1.037	1.371
West Virginia	1.457	1.064	1.549
Wisconsin	1.292	1.059	1.368
Wyoming	1.330	1.031	1.371
Average	0.948	1.043	0.989

Note: Rail transportation information for Alaska and Hawaii is not available in the BEA online database, so 49 states are used for this productivity analysis.

Table 7. Malmquist productivity and its decomposition in the pipeline transportation industry in the U.S., 2004-2011.

State	Efficiency change	Technological change	Productivity
Alabama	1.047	0.815	0.854
Alaska	1.107	0.816	0.903
Arizona	1.122	0.815	0.915
Arkansas	1.078	0.820	0.884
California	1.211	0.821	0.994
Colorado	1.061	0.815	0.865
Connecticut	1.061	0.815	0.865
Florida	0.896	0.815	0.730
Georgia	1.106	0.815	0.902
Idaho	1.122	0.816	0.916
Illinois	1.123	0.815	0.915
Indiana	1.079	0.820	0.885
Iowa	1.202	0.821	0.987
Kansas	1.037	0.815	0.846
Kentucky	1.080	0.815	0.880
Louisiana	0.930	0.815	0.758
Maine	1.208	0.815	0.984

Continued

Maryland	1.253	0.816	1.022
Massachusetts	1.265	0.815	1.032
Michigan	1.233	0.820	1.011
Minnesota	1.431	0.821	1.174
Mississippi	1.232	0.815	1.004
Missouri	1.337	0.815	1.089
Montana	1.171	0.815	0.954
Nebraska	1.097	0.815	0.894
Nevada	1.126	0.816	0.919
New Hampshire	1.144	0.815	0.933
New Jersey	1.081	0.820	0.887
New Mexico	1.170	0.821	0.960
New York	1.036	0.815	0.844
North Carolina	1.055	0.815	0.860
North Dakota	0.846	0.815	0.689
Ohio	0.964	0.815	0.785
Oklahoma	0.984	0.816	0.803
Oregon	1.013	0.815	0.826
Pennsylvania	0.995	0.820	0.816
Rhode Island	1.145	0.821	0.939
South Carolina	0.992	0.815	0.808
South Dakota	1.012	0.815	0.824
Tennessee	0.883	0.815	0.720
Texas	1.103	0.815	0.899
Utah	1.141	0.816	0.931
Virginia	1.162	0.815	0.947
Washington	1.137	0.820	0.933
West Virginia	1.242	0.821	1.019
Wisconsin	1.094	0.815	0.892
Wyoming	1.143	0.815	0.931
Average	1.100	0.817	0.898

Note: Pipeline transportation information for District of Columbia, Delaware, Hawaii, and Vermont is not available in the BEA online database, so 47 states are used for the productivity analysis.

increase of 2.3% in efficiency change and a decrease of 2.2% in technological change. Like the truck transportation industry, each water transportation industry in the 38 states shows all negative technological changes, but the productivity changes in the 18 states show growth. The following states having an average productivity growth of more than 10%: Arizona (18.1%), North Carolina (16.4%), South Carolina (15.3%), Pennsylvania (13.9%), Connecticut (13.9%), Rhode Island (13.2%), Ohio (11.1%), and Alaska (10.9%). **Figure 6** depicts the geographic representation of average productivity for 2004-2011 by state in the water transportation industry.

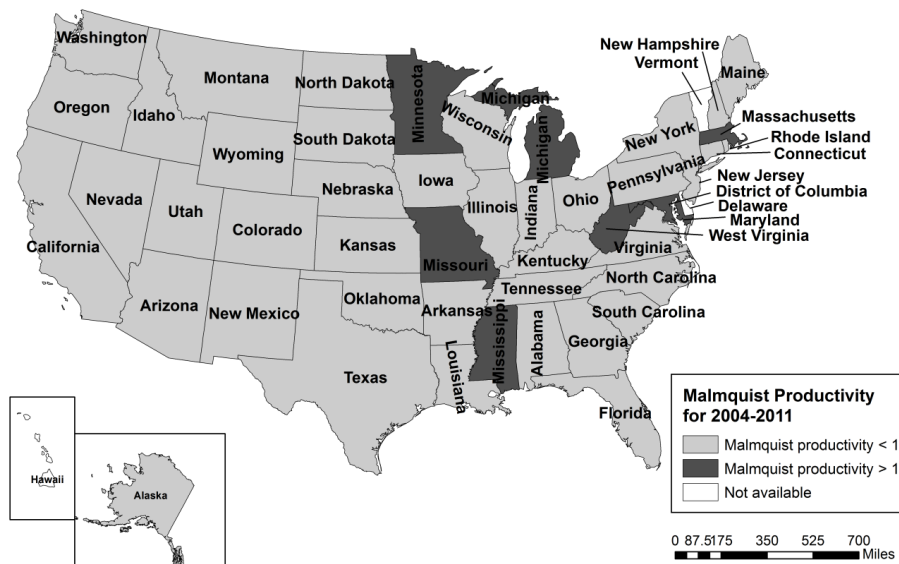


Figure 5. Geographic representation of average Malmquist productivity for 2004-2011 by state in the pipeline transportation industry.

Table 8. Malmquist productivity and its decomposition in the water transportation industry in the U.S., 2004-2011.

State	Efficiency change	Technological change	Productivity
Alabama	1.087	0.978	1.063
Alaska	1.147	0.967	1.109
Arizona	1.197	0.987	1.181
Arkansas	1.115	0.977	1.090
California	1.082	0.978	1.058
Connecticut	1.150	0.991	1.139
District of Columbia	1.051	0.969	1.018
Florida	1.078	0.980	1.056
Georgia	1.111	0.978	1.086
Hawaii	1.057	0.967	1.021
Illinois	1.031	0.987	1.017
Indiana	1.010	0.977	0.988
Iowa	1.000	0.978	0.978
Kentucky	1.000	0.991	0.991
Louisiana	0.849	0.969	0.822
Maine	0.864	0.980	0.846
Maryland	1.035	0.978	1.012
Massachusetts	1.002	0.967	0.968
Michigan	0.947	0.987	0.934
Mississippi	0.999	0.977	0.977

Continued

Missouri	0.973	0.978	0.952
New Jersey	0.915	0.991	0.907
New Mexico	0.993	0.969	0.962
New York	0.997	0.980	0.977
North Carolina	1.191	0.978	1.164
Ohio	1.149	0.967	1.111
Oregon	1.092	0.987	1.077
Pennsylvania	1.165	0.977	1.139
Rhode Island	1.158	0.978	1.132
South Carolina	1.164	0.991	1.153
Tennessee	0.974	0.969	0.943
Texas	0.992	0.980	0.972
Utah	0.951	0.978	0.930
Vermont	0.942	0.967	0.910
Virginia	0.918	0.987	0.906
Washington	0.883	0.977	0.864
West Virginia	0.891	0.978	0.871
Wisconsin	0.904	0.991	0.896
Average	1.023	0.978	1.001

Note: Water transportation information for Colorado, Delaware, Idaho, Kansas, Montana, Nebraska, Nevada, New Hampshire, Minnesota, North Dakota, Oklahoma, South Dakota, and Wyoming is not available in the BEA online database, so 38 states are used for the productivity analysis.

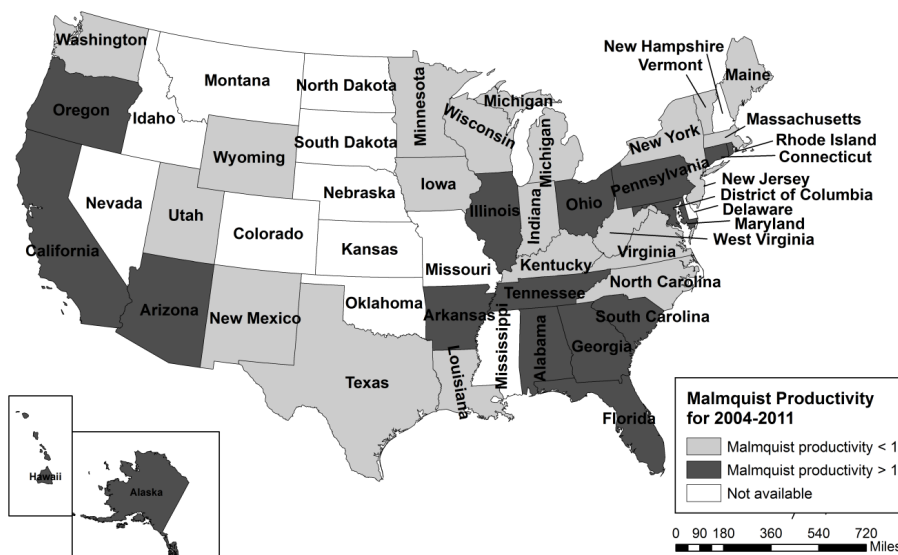


Figure 6. Geographic representation of average Malmquist productivity for 2004-2011 by state in the water transportation industry.

Table 9 summarizes the annual average productivity and efficiency and technological change in the five major transportation industries and the pooled transportation industry for 2004 to 2011. As is known, an unexpected global financial crisis occurred in 2007, 2008, and 2010, which negatively affected U.S. industry. As a result, each transportation industry had been growing at different rates corresponding to the U.S. economic recovery.

The major findings are as follows. First, the pooled transportation representing the U.S. transportation industry shows productivity growth of 21.7% in 2011 as well as a strong and positive trend except in the years of 2007, 2008, and 2010. Second, the airline transportation industry shows a severe drop in productivity growth during the years of the global financial crisis, but high productivity growth in 2005, 2009, and 2011. Third, the truck transportation industry grew in 2007 and 2010, but recently shows a decrease in productivity growth and even a decline in 2011 at 16.4%. Fourth, productivity growth in the rail transportation industry exponentially increased except in those three years. Indeed, the distinct productivity growth levels of 50.2% in 2006, 81.5% in 2009, and 91.6% in 2011 are surprising. Fifth, the pipeline transportation industry grew sharply until 2008, but after that point, productivity declines drifted. This industry show a productivity decline with the truck transportation industry in 2011. Finally, the water transportation industry on average shows at least 10% productivity growth out of the years of the financial crisis, but particularly almost close to zero in 2009. It is also ranked the second highest productivity growth in 2011 (37%). Overall, efficiency and technological change shows a mixed increase or decrease over time in each industry and the pooled transportation industry, but their productivities have predictable increasing or decreasing trends. **Figure 7** depicts the productivities of each transportation industry and the pooled transportation industry for 2005, 2006, 2009, and 2011.

5. Conclusions

The U.S. transportation industry contributes over one-tenth of U.S. GDP, and thus its productivity growth is importantly connected to the growth of the entire U.S. economy. In this study, we measured productivity growth in

Table 9. Productivity and efficiency and technological change in each industry and the pooled industry during the period of 2005 to 2011.

Productivity	2005	2006	2007	2008	2009	2010	2011	Average
Airline transportation	1.389	0.862	0.783	0.836	1.327	0.840	1.132	0.998
Truck transportation	0.642	1.322	1.039	0.872	1.208	1.105	0.836	0.978
Rail transportation	0.476	1.502	1.216	0.660	1.815	0.464	1.916	0.989
Pipeline transportation	0.494	1.035	1.087	1.921	0.752	0.829	0.707	0.898
Water transportation	1.176	1.121	0.870	0.917	0.990	0.708	1.370	1.001
Pooled transportation	0.662	1.485	0.831	0.951	1.291	0.848	1.217	1.005

Note: There is no base year to calculate productivity for 2004.

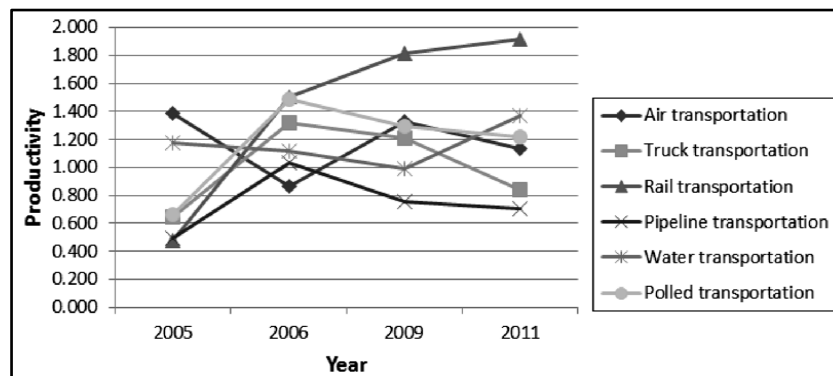


Figure 7. Annual average Malmquist productivities of each transportation industry and the pooled transportation industry for 2005, 2006, 2009, and 2011.

the five major transportation industries of airline, truck, rail, pipeline, and water as well as the pooled transportation industry for 2004–2011 and decomposed this growth into efficiency and technological change to provide its fundamental driving forces. This study separately found the results of average productivity for the eight years by state in each transportation industry and the annual average productivities for the transportation industries themselves. Although the average productivity growth by state in these transportation industries was on average close to zero or slightly increasing, the overall U.S. transportation industry grew with a strong and positive trend with noteworthy productivity growth of 21.7% in 2011, except that in the years of the global financial crisis in 2007, 2008, and 2010. The rail and water transportation industries had the first and second highest productivity growth in 2011, which might have been as a result of the growth in sustainable transport modes globally.

This study had a limitation based on the data used. The intermediate inputs for each state were estimated to find the best-possible approximation through the extent of taxes that each state collected; if original data on energy, materials, and purchased-service inputs in the BEA were available to the public, we could estimate more accurate results for productivity growth in the U.S. transportation industry.

Acknowledgements

This research was part of Jaesung Choi's dissertation. The authors would like to thank anonymous reviewers for their constructive comments.

References

- [1] Rodrigue, J.P. and Notteboom, T. (2013) *The Geography of Transport Systems*.
- [2] The United States Department of Transportation (2014) *Growth in the Nation's Freight Shipments*. http://www.rita.dot.gov/bts/sites/rita.dot.gov/bts/files/publications/freight_shipments_in_america/html/entire.html
- [3] Färe, R., Grosskopf, S., Lindgren, B. and Roos, P. (1992) Productivity Changes in Swedish Pharmacies 1980–1989: A Non-Parametric Malmquist Approach. *The Journal of Productivity Analysis*, **3**, 85–101. <http://dx.doi.org/10.1007/BF00158770>
- [4] Färe, R. and Grosskopf, S. (1994) Theory and Calculation of Productivity Indexes. In: *Models and Measurement of Welfare and Inequality*, Springer, Berlin, Heidelberg, New York, 921–940.
- [5] Färe, R., Grosskopf, S., Norris, M. and Zhang, Z.Y. (1994) Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries. *American Economic Review*, **84**, 66–83.
- [6] Färe, R., Grosskopf, S., Lindgren, B. and Roos, P. (1994) *Data Envelopment Analysis: Theory, Methodology, and Application*. Kluwer Academic Publishers, Dordrecht, 253–272.
- [7] Hjalmarsson, L., Kumbhakar, S.C. and Heshmati, A. (1996) DEA, DFA and SFA: A Comparison. *Journal of Productivity Analysis*, **7**, 303–327. <http://dx.doi.org/10.1007/BF00157046>
- [8] Celen, A. (2013) Efficiency and Productivity (TFP) of the Turkish Electricity Distribution Companies: An Application of Two-Stage (DEA&Tobit) Analysis. *Energy Policy*, **63**, 300–310. <http://dx.doi.org/10.1016/j.enpol.2013.09.034>
- [9] Farrell, M. (1957) The Measurement of Productive Efficiency. *Journal of the Royal Statistical Society*, **120**, 253–290. <http://dx.doi.org/10.2307/2343100>
- [10] Charnes, A., Cooper, W. and Rhodes, E. (1978) Measuring the Efficiency of Decision Making Units. *European Journal of Operational Research*, **2**, 429–444. [http://dx.doi.org/10.1016/0377-2217\(78\)90138-8](http://dx.doi.org/10.1016/0377-2217(78)90138-8)
- [11] Caves, D.W., Christensen, L.R. and Diewert, W.E. (1982) The Economic Theory of Index Numbers and the Measurement of Input, Output, and Productivity. *Econometrica*, **50**, 1393–1414. <http://dx.doi.org/10.2307/1913388>
- [12] Sueyoshi, T. (1992) Measuring Technical, Allocative and Overall Efficiencies Using a DEA Algorithm. *Journal of the Operational Research Society*, **43**, 141–155. <http://dx.doi.org/10.1057/jors.1992.19>
- [13] Ball, V., Lovell, C., Luu, H. and Nehring, R. (2004) Incorporating Environmental Impacts in the Measurement of Agricultural Productivity Growth. *Journal of Agricultural and Resource Economics*, **29**, 436–460.
- [14] Heng, Y., Lim, S.H. and Chi, J. (2012) Toxic Air Pollutants and Trucking Productivity in the US. *Transportation Research Part D*, **17**, 309–316. <http://dx.doi.org/10.1016/j.trd.2012.01.001>
- [15] Sueyoshi, T. and Goto, M. (2013) DEA Environmental Assessment in a Time Horizon: Malmquist Index on Fuel Mix, Electricity and CO₂ of Industrial Nations. *Energy Economics*, **40**, 370–382. <http://dx.doi.org/10.1016/j.eneco.2013.07.013>
- [16] Chen, Y. and Ali, A. (2004) DEA Malmquist Productivity Measure: New Insights with an Application to Computer Industry. *European Journal of Operational Research*, **159**, 239–249. [http://dx.doi.org/10.1016/S0377-2217\(03\)00406-5](http://dx.doi.org/10.1016/S0377-2217(03)00406-5)

- [17] Liu, F. and Wang, P. (2008) DEA Malmquist Productivity Measure: Taiwanese Semiconductor Companies. *International Journal of Production Economics*, **112**, 367-379. <http://dx.doi.org/10.1016/j.ijpe.2007.03.015>
- [18] Qazi, A. and Zhao, Y.L. (2012) Productivity Measurement of Hi-Tech Industry of China Malmquist Productivity Index-DEA Approach. *Procedia Economics and Finance*, **1**, 330-336. [http://dx.doi.org/10.1016/S2212-5671\(12\)00038-X](http://dx.doi.org/10.1016/S2212-5671(12)00038-X)
- [19] Coelli, T. (1996) A Guide to DEAP Version 2.1: A Data Envelopment Analysis Program. Centre for Efficiency and Productivity Analysis (CEPA), Armidale.
- [20] The United States Bureau of Economic Analysis (2013) Interactive Data. <http://www.bea.gov/itable/>
- [21] The United States Department of Commerce (2014) Industry Data. http://www.bea.gov/iTable/index_industry_gdpIndy.cfm
- [22] Daniel, W.W. (1990) Applied Nonparametric Statistics. Duxbury, Pacific Grove.

JIT Mixed-Model Sequencing Rules: Is There a Best One?

Patrick R. McMullen

School of Business, Wake Forest University, Winston-Salem, North Carolina, USA
Email: mcmullpr@wfu.edu

Received 3 November 2014; revised 29 November 2014; accepted 10 December 2014

Copyright © 2015 by author and Scientific Research Publishing Inc.
This work is licensed under the Creative Commons Attribution International License (CC BY).
<http://creativecommons.org/licenses/by/4.0/>



Open Access

Abstract

This research effort compares four sequencing rules intended to smooth production scheduling for mixed-model production systems in a Just-in-Time/Lean manufacturing environment (“JIT” hereafter). Each rule intends to schedule mixed-model production in such a way that manufacturing flexibility is optimized in terms of system utilization, units completed, average in-process inventory, average queue length, and average waiting time. A simulation experiment, where the various sequencing rules are tested against each other in terms of the above production measures, shows that three of the sequencing rules essentially offer the same performance, whereas one of them shows more variation.

Keywords

JIT/Lean Manufacturing, Scheduling, Sequencing, Enumeration, Simulation

1. Introduction

In a JIT/Lean manufacturing environment, it is important to schedule production in such a way that units are manufactured in direct proportion to their demand. Otherwise, in-process inventories accumulate, throughput time increases, schedule compliance suffers, all resulting in sub-optimal performance [1]. Consider the simple example where four units of Item A are demanded, two units of Item B are demanded and one unit of Item C is demanded. One possible schedule is as follows: AAAABBC. While changeovers are minimized, units are not sequenced proportional to demand. The following schedule would be better in terms of “smoothing out” production in terms of demand: ABACABA [2].

There are various strategies and algorithms used to find the “best” sequence in terms of smoothing out production. These sequencing algorithms vary in terms of details, but they all share the same intent of smoothing out sequencing as much as possible.

This paper explores four of the more common sequencing rules, uses them to sequence mixed-model production schedules, simulates production schedules under various conditions, and analyzes the performance of the various rules.

2. Sequencing Rules

Four sequencing rules are investigated for this research effort. Prior to presenting the individual rules, a few definitions are needed.

Symbol	Definition
i	Index for all items
n	Number of all items ($i=1,2,\dots,n$)
k	Index for each unique item
d_i	Demand for unique item i ($k=1,2,\dots,d_i$)
D	Total number of items (or total demand)
$\bar{\Delta}_i$	Average gap between units of each unique item
Δ_k^i	Actual gap between positions $k+1$ and k for item i
x_{ik}	The number of units of i produced through the k^{th} sequence position

As an example for the sequence: ABACABA, we have Δ_k^i values of (2, 2, 2, 1) for $i=1$ (Item A), (4, 3) for $i=2$ (Item B), and (7) for $i=3$ (Item C). When we calculate these Δ_k^i values, we assume that the sequence cycles over and over. For the $\bar{\Delta}_i$ values, we simply use $D/d_i (\forall i)$, yielding values of (7/4, 7/2, 7/1) for this particular problem.

2.1. Minimize Maximum Response Gap (MRG)

The first objective function to be studied is the minimization of the maximum response time for a sequence [3]. Mathematically, this is as follows:

$$\min : \max_i \left(\max_k \left| \Delta_k^i - \bar{\Delta}_i \right| \right) \quad (1)$$

For our example problem, this objective function value would be as follows:

$$\max \left(\max (|2-7/4|, |2-7/4|, |2-7/4|, |1-7/4|), \max (|4-7/2|, |3-7/2|), \max (|7-7/1|) \right),$$

which reduces to: $\max (0.75, 0.50, 0.0) = 0.75$.

2.2. Minimize Average Gap Length (AGL)

The next objective to be studied is the minimization of the average distance between the actual gap and the average gap [4] [5]. Mathematically, this is as follows:

$$\min : \sum_{i=1}^n \sum_{k=1}^{d_i} \left[\left| \Delta_k^i - \bar{\Delta}_i \right| \right] / D \quad (2)$$

The example problem above, the objective function value would be as follows:

$$\left[|2-7/4| + |2-7/4| + |2-7/4| + |1-7/4| + |4-7/2| + |3-7/2| + |7-7/1| \right] / 7, \text{ resulting in a value of } 0.3571.$$

2.3. Minimize Gap Variation (VAR)

The next objective to be studied is the minimization of gap length variation [6]. Mathematically, this objective is as follows:

A	B	A	C	A	B	A
1	1	2	2	3	3	4
0	1	1	1	1	2	2
0	0	0	1	1	1	1

$$\text{Min} : \sum_{i=1}^n \sum_{k=1}^{d_i} (\Delta_k^i - \bar{\Delta}_i)^2 \tag{3}$$

Using the example problem above, the objective function value would be: $(2-7/3)^2 + (2-7/3)^2 + (2-7/3)^2 + (1-7/3)^2 + (4-7/2)^2 + (3-7/2)^2 + (7-7/1)^2$. This calculation results in a value of 1.25.

2.4. Minimize Usage Rate (USAGE)

The final objective function to be explored is the minimization of the usage rate—keeping as constant as possible in assigning units for sequencing [7]. Mathematically, this is as follows:

$$\text{Min} : \sum_{k=1}^D \sum_{i=1}^{d_i} \left(x_{ik} - k \frac{d_i}{D} \right)^2 \tag{4}$$

For the example problem, the objective function value is 1.7143, when using x_{ik} values reflecting the sequence:

A	B	A	C	A	B	A
1	1	2	2	3	3	4
0	1	1	1	1	2	2
0	0	0	1	1	1	1

3. Experimentation

To determine which of the sequencing rules is most effective in terms of the JIT/Lean objectives mentioned previously, experimentation is conducted. Several problem sets are simulated according to their best sequence in terms of the objectives described above, simulation is performed, data is collected from the simulation, and analysis is made in an attempt to differentiate performance among the four presented objectives [8].

3.1. Problem Sets

Eight problem sets are used for experimentation, starting with a small problem and having the problems grow large to the point where finding the optimal sequencing (via complete enumeration) in terms of the objective function values becomes computationally intractable. **Table 1** shows the product mix details of the eight problem sets used, and the number of total permutations required for compute enumeration.

Complete enumeration is used for each problem set so that the optimal values for each objective function shown above are obtained. It is intended to show each objective function in its “best possible light”.

For each unique item, a processing time for the single-stage simulation has been assigned. In actuality, three different processing time templates have been assigned to each unique item: ascending processing times, descending processing times, and randomly assigned processing times on the uniformly-distributed interval (2, 10). **Table 2** summarizes the processing times for each of the three variants, along with simulation settings.

3.2. Simulation Outputs

Several output measures are used to determine the performance of the sequencing rules. They are as follows:

- Utilization—the average amount of time the system is busy.
- Units completed—the average number of units completed by the system.
- Average WIP level—the average number of units in the system at any given time.

Table 1. Details of problem sets.

Problem Set	Product Mix (d_A, d_B, d_C, d_D, d_E)	Total Permutations
1	(3, 2, 2)	210
2	(3, 2, 2, 2)	7560
3	(4, 2, 2, 2)	1,247,400
4	(5, 3, 2, 2, 2)	15,135,120
5	(6, 3, 2, 2, 2)	37,837,800
6	(6, 4, 2, 2, 2)	151,351,200
7	(6, 4, 3, 2, 2)	857,656,800
8	(6, 4, 3, 3, 2)	5,145,940,800

Table 2. Simulation details.

Item	Ascending Processing Time	Descending Processing Time	Randomly Assigned Processing Time
A	0.50 min	2.50 min	2.97 min
B	1.00 min	2.00 min	5.43 min
C	1.50 min	1.50 min	7.11 min
D	2.00 min	1.00 min	9.87 min
E	2.50 min	0.50 min	5.43 min
Sim. Warmup Time	4 h	4 h	50 h
Simulation Time	8 h	8 h	100 h

- Average Queue Length—average number of units waiting to be processed.
 - Average Waiting Time—average amount of time a unit spends waiting to be processed.
- These performance measures are actual outputs from the simulation.

3.3. Design of Experiment

The general research question pursued is to determine whether or not the sequencing rules have an effect on the simulation performance measures. This question can be adequately addressed via Single-Factor ANOVA, with the sequencing rule as the experimental factor (of which there are four levels), and the simulation-based performance measure as the response variable.

Because there are eight different production models, three different processing time templates, and five different simulation-based performance measures, there are $(8)(3)(5) = 120$ different analyses to perform. Each of the (120) analyses utilize (25) simulation replications.

4. Experimental Results

Tables 3-10 show the results of the experiments for each unique analysis, specifically including the mean for each factor level, along with the F-statistics and associated p-value for each experiment. These tables show that the sequencing rule has an effect on the performance measure of interest (26) times of the (120) experiments conducted, using an $\alpha = 0.05$ level of significance. Of these (26) times, USAGE is a superior performer compared to the other three (8) times, and is an inferior performer compared to the other three (17) times. There is one other occasion where the sequencing rule has an effect on a performance measure of interest, but the difference is not due to USAGE.

Table 11 shows the similarity between all four of the sequencing objectives, based upon the sequences obtained via complete enumeration of all possible sequences for all (120) problems.

As one can see, there is a great deal of similarity between the MRG, AGL and VAR objective functions, while the USAGE objective function is absolutely unique from the other three. This is a reasonable explanation as to why USAGE is the biggest contributor to the significance of the sequencing rule.

Table 3. Model 1 results.

Utilization						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	0.8496	0.848500	0.846880	0.824560	1.0424	0.3764
Descending	0.8520	0.852016	0.852016	0.854600	0.0053	0.9995
Random	0.8379	0.837924	0.837924	0.833301	0.0769	0.9724
Units Completed						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	217.64	195.64	217.56	216.40	10.673	<0.0001
Descending	99.16	99.19	99.16	99.76	0.0248	0.9947
Random	514.88	514.88	514.88	515.24	0.0014	>0.9999
Average Work-in-Process Inventory Level						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	3.877236	3.739948	3.712024	3.406172	0.2991	0.8260
Descending	3.641352	3.641352	3.641352	3.365696	0.0708	0.9754
Random	3.45626	3.45626	3.45626	3.30382	0.0562	0.9824
Average Queue Length						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	3.027608	2.891458	2.865168	2.581624	0.148	0.9308
Descending	2.789324	2.789324	2.789324	2.511084	0.0758	0.973
Random	2.618324	2.618324	2.618324	2.470504	0.0553	0.9828
Average Waiting Time						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	0.055596	0.059252	0.052648	0.046916	0.8651	0.4613
Descending	0.104508	0.104508	0.104508	0.093980	0.1095	0.9544
Random	0.248864	0.248864	0.248864	0.235296	0.0670	0.9773

Table 4. Model 2 results.

Utilization						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	0.846599	0.845988	0.845988	0.955528	2.986	0.0350
Descending	0.861836	0.861836	0.861836	0.853848	0.057	0.9820
Random	0.828568	0.831280	0.831280	0.831256	0.0233	0.9952
Units Completed						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	173.76	173.76	173.76	164.80	2.986	0.03498
Descending	113.28	113.28	113.28	112.64	0.0196	0.9962
Random	416.84	416.84	416.84	415.32	0.0299	0.9930
Average Work-in-Process Inventory Level						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	3.65082	3.65082	3.65082	10.72509	20.748	<0.0001
Descending	3.976532	3.976532	3.976532	3.603900	0.0947	0.9628
Random	3.156824	3.191032	3.191032	3.332632	0.0939	0.9633
Average Queue Length						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	2.804836	2.804836	2.804836	9.769538	20.488	<0.0001
Descending	3.114712	3.114712	3.114712	2.750044	0.0942	0.9630
Random	2.714440	2.359736	2.359736	2.501376	0.3837	0.7650
Average Waiting Time						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	0.063588	0.063588	0.063588	0.228816	23.256	<0.0001
Descending	0.103420	0.103420	0.103420	0.089684	0.1718	0.9152
Random	0.182500	0.279252	0.279252	0.293824	2.7484	0.04704

Table 5. Model 3 results.

Utilization						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	0.851456	0.851456	0.851456	0.860812	0.0966	0.9618
Descending	0.866020	0.866020	0.866020	0.867912	0.0035	0.9997
Random	0.831056	0.831056	0.831056	0.854252	1.4280	0.2394
Units Completed						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	152.60	152.60	152.60	154.28	0.0952	0.9625
Descending	123.92	123.92	123.92	123.08	0.0312	0.9925
Random	442.04	442.04	442.04	455.68	1.8033	0.1517
Average Work-in-Process Inventory Level						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	4.232124	4.232124	4.232124	3.828688	0.115	0.9511
Descending	4.698984	4.698984	4.698984	4.141492	0.2101	0.8892
Random	3.281408	3.281408	3.281408	4.152180	1.7745	0.1572
Average Queue Length						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	3.380676	3.380676	3.380676	2.967872	0.1254	0.9449
Descending	3.832976	3.832976	3.832976	3.273564	0.2200	0.8823
Random	2.450344	2.450344	2.450344	3.297908	1.7537	0.1612
Average Waiting Time						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	0.085080	0.085080	0.085080	0.076388	0.1017	0.9588
Descending	0.117624	0.117624	0.117624	0.099628	0.2993	0.8258
Random	0.272304	0.272304	0.272304	0.348268	1.5162	0.2152

Table 6. Model 4 results.

Utilization						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	0.844088	0.855096	0.855096	0.856044	0.148	0.9308
Descending	0.860512	0.863156	0.863156	0.865564	0.0158	0.9973
Random	0.8299692	0.858096	0.858096	0.832084	2.6878	0.05073
Units Completed						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	163.72	163.12	163.12	164.00	0.0238	0.9950
Descending	118.44	117.48	117.48	118.20	0.0445	0.9874
Random	460.04	460.20	460.20	459.80	0.0015	>0.9999
Average Work-in-Process Inventory Level						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	4.103420	4.240428	4.240428	4.033872	0.0266	0.9940
Descending	4.131964	4.074024	4.074024	3.803624	0.0678	0.9770
Random	3.326052	3.974592	3.794592	3.441616	0.5260	0.6654
Average Queue Length						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	3.259328	3.385324	3.385324	3.177820	0.0268	0.994
Descending	3.271460	3.210864	3.210864	2.938036	0.0726	0.9745
Random	2.496064	2.936480	2.936480	2.609532	0.4816	0.6959
Average Waiting Time						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	0.077840	0.080388	0.080388	0.075748	0.0274	0.9939
Descending	0.104472	0.102820	0.102820	0.094020	0.0927	0.9640
Random	0.266704	0.313496	0.313496	0.275472	0.6541	0.5823

Table 7. Model 5 results.

Utilization						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	0.931072	0.931072	0.931072	0.847904	9.2351	<0.0001
Descending	0.854372	0.854373	0.854372	0.862352	0.0533	0.9837
Random	0.877564	0.877564	0.877564	0.809252	16.531	<0.0001
Units Completed						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	168.80	168.80	168.80	170.64	0.139	0.9365
Descending	114.56	114.56	114.56	114.28	0.0036	0.9997
Random	515.28	515.28	515.28	474.76	17.051	<0.0001
Average Work-in-Process Inventory Level						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	9.059772	9.059772	9.059772	4.347732	3.0445	0.03251
Descending	3.751952	3.751952	3.751952	4.121096	0.1250	0.9451
Random	4.646360	4.646360	4.646360	2.961892	3.0055	0.03414
Average Queue Length						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	8.128708	8.128708	8.128708	3.499828	2.975	0.03546
Descending	2.897572	2.897572	2.897572	3.258720	0.1250	0.9451
Random	3.768800	3.768800	3.7688	2.152648	2.8450	0.0417
Average Waiting Time						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	0.187900	0.187900	0.187900	0.080068	3.3589	0.02197
Descending	0.095696	0.095696	0.095696	0.105032	0.1100	0.9540
Random	0.357648	0.357648	0.357648	0.222064	2.7119	0.04923

Table 8. Model 6 results.

Utilization						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	0.848248	0.848248	0.852792	0.856612	0.0684	0.9766
Descending	0.866332	0.866332	0.850972	0.853360	0.2363	0.8708
Random	0.838636	0.838636	0.780808	0.834900	15.297	<0.0001
Units Completed						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	171.04	171.04	172.48	171.12	0.0663	0.9776
Descending	113.56	113.56	113.88	114.00	0.0091	0.9988
Random	952.20	952.20	951.56	952.32	0.0019	0.9999
Average Work-in-Process Inventory Level						
Approach	MRG	AGL	VAR	USAGE	F	<i>P</i>
Ascending	4.298532	4.298532	4.038416	4.518884	0.1322	0.9407
Descending	3.911632	3.911632	3.533304	3.809464	0.1459	0.9321
Random	3.561468	3.561468	2.507636	3.375052	5.2782	0.002061
Average Queue Length						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	3.450292	3.450292	3.185640	3.662272	0.1363	0.9381
Descending	3.045288	3.045288	2.682336	2.956096	0.1417	0.9347
Random	2.722860	2.722860	1.726816	2.540156	4.9644	0.003022
Average Waiting Time						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	0.078272	0.078272	0.073752	0.083284	0.1248	0.9453
Descending	0.101656	0.101656	0.089936	0.097980	0.1891	0.9036
Random	0.282624	0.282624	0.179864	0.264312	5.7694	0.001137

Table 9. Model 7 results.

Utilization						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	0.749796	0.749796	0.749796	0.838384	9.0906	<0.0001
Descending	0.848884	0.848884	0.848884	0.784623	3.5972	0.01633
Random	0.762016	0.762016	0.762016	0.784824	3.3313	0.02274
Units Completed						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	168.68	168.68	168.68	170.24	0.0741	0.9738
Descending	114.80	114.80	114.80	115.08	0.0034	0.9997
Random	933.84	933.84	933.84	933.16	0.002	0.9999
Average Work-in-Process Inventory Level						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	2.372900	2.372900	2.372900	3.787576	7.008	0.0003
Descending	3.764943	3.764932	3.764932	2.709792	1.2536	0.2947
Random	2.303660	2.303660	2.303660	2.703868	2.8364	0.04215
Average Queue Length						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	1.623116	1.623116	1.623116	2.949196	6.6761	0.00038
Descending	2.916052	2.916052	2.916052	1.925176	1.1638	0.3277
Random	1.541628	1.541628	1.541628	1.919048	2.7437	0.04731
Average Waiting Time						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	0.037968	0.037968	0.037968	0.06894	7.7625	0.00011
Descending	0.095328	0.095328	0.095328	0.06292	1.6310	0.1873
Random	0.163836	0.163836	0.163836	0.203252	3.1971	0.02688

Table 10. Model 8 results.

Utilization						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	0.764568	0.770580	0.770580	0.808764	1.9186	0.1317
Descending	0.834308	0.834308	0.834308	0.804652	1.1765	0.3228
Random	0.778916	0.778916	0.778916	0.789568	0.4432	0.7227
Units Completed						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	163.00	163.00	163.00	163.36	0.0041	0.9996
Descending	118.24	117.60	117.60	117.40	0.0240	0.9950
Random	891.08	891.08	891.08	892.40	0.0067	0.9992
Average Work-in-Process Inventory Level						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	2.740600	2.831356	2.831356	3.157008	0.2901	0.8324
Descending	3.467116	3.294740	3.294740	2.939416	0.4285	0.7330
Random	2.516672	2.516672	2.516672	2.835504	0.9569	0.4164
Average Queue Length						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	1.976036	2.060772	2.060772	2.348252	0.2449	0.8648
Descending	2.621868	2.46036	2.460436	2.134756	0.3938	0.7578
Random	1.737764	1.737764	1.737764	2.045956	0.9672	0.4116
Average Waiting Time						
Approach	MRG	AGL	VAR	USAGE	F	<i>p</i>
Ascending	0.046884	0.04988	0.049488	0.056260	0.3272	0.8057
Descending	0.084648	0.079688	0.079688	0.068972	0.5240	0.6668
Random	0.192992	0.192992	0.192992	0.226984	1.1195	0.3451

Table 11. Similarity matrix.

	MRG	AGL	VAR	USAGE
MRG	x	x	x	x
AGL	73.23%	x	x	x
VAR	60.83%	86.67%	x	x
USAGE	0%	0%	0%	x

5. Concluding Comments

An experiment was conducted to see if four popular sequencing rules have any effect on performance measures important to JIT/Lean manufacturing systems. Eight different problems were investigated, each with three processing time arrangements, and five different JIT/Lean manufacturing performance measures to study. For each of the four sequencing rules, complete enumeration of all feasible permutations was generated to find the “best” sequence in terms of the objective function associated with each sequencing rule. This was done to show each sequencing rule in its “best possible light”.

Experimentation shows statistical significance of the sequencing rule (26) times out of a possible (120) times. The USAGE sequencing rule is the reason for the significant difference in means (25) of these (26) times—(17) of these (25) times USAGE provides inferior results than the other three sequencing rules. USAGE is the most unique of the other sequencing rules and provides less consistent results as compared to the other three. This should not come as a surprise because the USAGE objective function only looks at a single instance of the sequence, whereas the other three sequencing rules explore the cyclic nature of the sequence—multiple instances of the repeated sequence. The upshot of this is that USAGE is a higher risk strategy than the others.

Every research effort provides opportunities for further exploration. This is no exception. Longer production sequences would be helpful if there is some way around the combinatorial limitations that exist at present. Additionally, multiple-stage simulated production runs might also yield some interesting results.

References

- [1] Goldratt, E.M. and Cox, J. (1992) *The Goal: A Process of Ongoing Improvement*. North River Press, North Barrington.
- [2] McMullen, P.R. (1998) JIT Sequencing for Mixed-Model Assembly Lines with Setups Using Tabu Search. *Production Planning & Control*, **9**, 504-510. <http://dx.doi.org/10.1080/095372898233984>
- [3] Kanet, J.J. (1981) Minimizing the Average Deviation of Job Completion Times About a Common Due Date. *Naval Research Logistics Quarterly*, **28**, 643-651. <http://dx.doi.org/10.1002/nav.3800280411>
- [4] Garcia-Villoria, A. and Pastor, R. (2013) Minimising Maximum Response Time. *Computers & Operations Research*, **40**, 2314-2321. <http://dx.doi.org/10.1016/j.cor.2013.03.014>
- [5] Salhi, S. and Garcia-Villoria, A. (2012) An Adaptive Search for the Response Time Variability Problem. *Journal of the Operational Research Society*, **63**, 597-605. <http://dx.doi.org/10.1057/jors.2011.46>
- [6] Hermann, J.W. (2007) *Generating Cyclic Fair Sequences Using Aggregation and Stride*. The Institute for Systems Research, ISR Technical Report 2007-12.
- [7] Miltenburg, J. (1989) Level Schedules for Mixed-Model Assembly Lines in Just-in-Time Production Systems. *Management Science*, **35**, 192-207. <http://dx.doi.org/10.1287/mnsc.35.2.192>
- [8] Kelton, D.W., Sadowski, R.P. and Sturrock, D.T. (2004) *Simulation with Arena*. 3rd Edition, McGraw-Hill Higher Education, Boston.

Assessing the Relative Efficiency of Health Systems in Sub-Saharan Africa Using Data Envelopment Analysis

Samuel Ambapour

Institute National de la Statistique, Brazzaville, Republic of Congo
Email: ambapour_samuel@yahoo.fr

Received 2 November 2014; accepted 22 November 2014; published 13 January 2015

Copyright © 2015 by author and Scientific Research Publishing Inc.
This work is licensed under the Creative Commons Attribution International License (CC BY).
<http://creativecommons.org/licenses/by/4.0/>



Open Access

Abstract

We assess the relative efficiency of health systems of 35 countries in sub-Saharan Africa using Data Envelopment Analysis. This method allows us to evaluate the ability of each country to transform its sanitary “inputs” into health “outputs”. Our results show that, on average, the health systems of these countries have an efficiency score between 72% and 84% of their maximum level. We also note that education and density of population are factors that affect the efficiency of the health system in these countries.

Keywords

Technical Efficiency, Data Envelopment Analysis, Health System

1. Introduction

Health is now seen as a component of human capital the same way as education and nutritional status [1]-[4]. According to these authors, everyone has an initial health stock that depreciates with age, but can be maintained or even appreciated by combining individual health care and education, and according to the time available. Moreover, according to a study by the World Bank (World Bank, 1993) at least four reasons support the assertion that a healthy individual is more productive and contributes more to economic growth.

- Health limits the loss of production because of the impact of disease on labor.
- It allows exploiting the natural resources that were largely inaccessible because they are located in infested areas.
- It increases the rate of school attendance and allows children to assimilate better the lessons learned.
- Finally, health frees for other purposes, resources that would have served otherwise to provide care to the

How to cite this paper: Ambapour, S. (2015) Assessing the Relative Efficiency of Health Systems in Sub-Saharan Africa Using Data Envelopment Analysis. *American Journal of Operations Research*, 5, 30-37.
<http://dx.doi.org/10.4236/ajor.2015.51003>

sick.

The impact of health on the well-being and overall health of a country probably justifies the huge investments of the states in this area. Indeed, in 1990, global spending on health was evaluated at \$1700 billion [5] with more than 1000 billion from states; representing 60% of the total. In developing countries (Africa, Asia, Latin America), these costs were estimated at \$170 billion, 50% funded by the states.

The role and the importance of health systems in the success of health outcomes are now well established. The issues that remain to investigate are, among other things, why some health systems can be considered more effective than others, and what explain the differences in countries' health systems.

The purpose of this paper is to shed some more light on this issue that, to our knowledge, has received little attention in the literature. This relative paucity of literature on the subject is associated, according to some authors (for example, [6] or [7]), to the challenges posed by the comparison of different health systems because, *inter alia*, of the following reasons:

1) The definition of health proposed by the World Health Organization (WHO) is, according to [8], useless for all practical purposes, "a perfect state of complete physical, mental and social well-being, not just the absence of disease or illness".

2) There are many measures of health status (see, for example, [6] or [9]), especially if we compare individual health indicators, such as "health utilities index" that, as argued by [7], are unfortunately based on functional capacity concepts rather than on performance.

This second argument should be tempered because, since 2000, a bold demarche for developing a composite index measuring the performance of health systems was conducted by the World Health Organization [10]. It's an index that determines the overall performance of a health system based both on the level of progress of each country with respect to a number of objectives and on the distribution of the health conditions in the population. Five criteria are generally used for this purpose: 1) The general health; 2) The distribution of this health condition; 3) The responsiveness of the health system; 4) The distribution of responsiveness; 5) The fairness of financial contributions. Unfortunately, as pointed out by [11], the quality of this synthetic indicator, as well as composite indexes calculated by the United Nations Development Programme (UNDP) namely, the Human Development Index (HDI) or the Human Poverty Index (HPI), is often questioned by statisticians and economists, both in the mathematical formulation as well as in the reliability of the statistics used.

In this paper, we compare and attempt to provide an explanation on the inefficiencies of health systems of 35 countries in sub-Saharan Africa. Our comparative analysis of health systems is based on the concept of efficiency obtained through Data Envelopment Analysis (DEA). This concept is related to the production function that shall be defined as the technical interrelationship which results in the maximum output for a combination of production factors and a given technology. This is somehow the ability of each country to transform its sanitary inputs in health outputs [12]. Beyond this definition, this function is also conceived as a frontier or a standard of comparison for assessing efficiency. In other words, the health system of a country will be considered efficient when the combination of outputs and inputs is located on the frontier.

Several reasons justify the appropriateness of the DEA in this study.

1) The popularity of this technique in the field of health lies in its ability to take into account the specificities of the sector such as the complexity of the technology (multi-product/multi-factors) and the absence of true price both for the outputs and for the inputs [13].

2) It's suggested for the analysis of complex or non-profit organizations such as public services. As pointed out by [14], it's close to the work of Leibenstein of X-inefficiency. Indeed, with DEA we can also characterize an output lying inside the Pareto optimal production frontier by stipulating that the hidden inefficiencies come from two sources: 1) the externalities inherent in the economic system or, more generally, to the political and social environment and 2) the non-apparent production factors or not taken into account by the model and thus related to the company's management [15].

Note that the DEA method was applied in health sector by many other authors, including [16]-[18]. However, in these applications, the analysis is usually at the micro level, that is to say, at the hospital level. The objective is then to evaluate the performance of a hospital in comparison to others [16]. This comparison is sometimes made depending on the status: not-for-profit versus for profit private organizations [17] [18]. It also happens to compare, according to their seniority, the practice of physicians within the same hospital [19].

Our study differs from previous at least on two points:

1) Our analysis is at a more macro level since we compare different countries' health systems, and not within

the same country. We seek to build an international production frontier in the health sector. For each country, we consider all hospitals as a single production unit.

2) In addition, this study is, to our knowledge, one of the first uses of the DEA method to compare health systems of countries in sub-Saharan Africa.

The rest of this article is organized as follows: Section 2 is devoted to the presentation of the DEA method. In Section 3, we present our results of the evaluation of the technical efficiency of the health systems of 35 countries of sub-Saharan Africa. Thus evaluated, the efficiency depends on the specific environment of each country. To provide explanatory elements of the efficiency scores of the different countries, we establish a relationship between the level of efficiency and certain strategic or environmental variables. Our concluding remarks are provided in Section 4.

2. Methodology

We apply DEA to assess the performance of health systems of 35 countries in sub-Saharan Africa. In this section, we first present the DEA and then describe our data and variables.

2.1. The DEA Method

DEA is a non-parametric method initially developed by [20] to evaluate the relative efficiency of the decision making units (DMU) of non-profit institutions, or of the public sector which use a group of similar inputs to produce a group of outputs. The DEA method measures the efficiency of a DMU “*o*” compared with the set of “*n*” DMUs in a given sample. The aim is to establish a level of relative efficiency θ ($0 \leq \theta \leq 1$) for each DMU by comparing its input and output quantities with those of other DMUs.

The efficiency in DEA can be characterized in two ways: the input orientation which supposes a minimization of inputs for a given level of outputs and the output orientation which assumes a maximization of the outputs for a given level of inputs. It's also possible to consider constant or variable returns to scale. Our analysis is based on the input minimization model with the assumption of variable returns to scale.

Indeed, minimizing inputs seems appropriate because:

1) One considers that, as in the case of public services, the services provided by the state to citizens are exogenous.

2) Resource utilization by the countries studied is generally carried out in a difficult budgetary situation.

3) Based on our data, input values are more dispersed than those of outputs. Therefore, minimizing inputs should allow better discrimination of efficiency scores of countries' health system.

Besides, the assumption of variable returns to scale can be justified by the fact that it is more general, but also because of our data. Indeed, it's difficult to identify scale inefficiencies in aggregate data as is the case in this study. See [21] for a full discussion of the DEA methods.

The model we have estimated is formally expressed below. All annotations are adopted from [21] and [22].

$$\min_{\theta, \lambda} \theta \quad (1)$$

Subject to:

$$\sum_{j=1}^n \lambda_j X_{ij} \leq \theta X_{io}, \quad i = 1, 2, \dots, m \quad (2)$$

$$\sum_{j=1}^n \lambda_j Y_{rj} \geq Y_{ro}, \quad r = 1, 2, \dots, s \quad (3)$$

$$\sum_{j=1}^n \lambda_j = 1, \quad j = 1, 2, \dots, n \quad (4)$$

$$\lambda_j \geq 0 \quad (5)$$

where DMU_o represents one of the “*n*” DMUs under evaluation. x_{io} and y_{ro} are respectively the i^{th} input and the r^{th} output of the DMU_o . s = the number of outputs produced by the DMU; m = number of inputs. θ^* ($\min\theta$) is a scalar which represents the score of the technical efficiency allotted to the unit under evaluation and is interpreted as the coefficient of the production level attained by the latter. λ is a weighting allotted to DMUs which

helps to determine the envelope formed by efficient DMUs ($\theta = 1$).

2.2. Describing the Sample and the Variables

Our data come from the World Bank database [23]. It covers the 1990-1999 periods and involves 35 countries in sub-Saharan Africa.

With aggregated data as ours, we choose as outputs: life expectancy at birth, infant mortality per thousand births and the mortality rate for children under five. These are also some of the outputs generally considered to calculate composite indices measuring the performance of health systems like that of the World Health Organization (WHO, 2000) or of the UNDP (HDI, HPI).

Regarding inputs, like many other authors [16] [17] [19] [22], we distinguish between labor inputs and capital inputs. The Labor is measured by the number of doctors per 1000 inhabitants. The capital stock is represented by the number of hospital beds per 1000 inhabitants and health expenditures per capita.

To check the sensitivity of our results, we analyze three specifications of the DEA model obtained by different combinations of inputs and outputs (Table 1). The first two specifications differ only on the outputs. In the first model (DEA1), life expectancy at birth and mortality rates of children under five were selected as outputs. In the second model (DEA2), only infant mortality per thousand births was selected as output. Finally, in the third model (DEA3), we select health expenditures as single input.

In the next section, we present the results obtained from these different DEA specifications.

3. Results

First, we present the efficiency scores of the three DEA specifications. Next, like several other authors (e.g. [24] and [25]) we use, in a second stage, a Tobit regression to analyze the impact of some exogenous factors on the DEA efficiency scores.

3.1. The Efficiency Scores

The efficiency scores are shown in Table 2. They were calculated using DEAP software developed by [26]. The complement to 1 of each efficiency score represents the possible proportional reduction of inputs without any reduction of the output levels. In other words, a country that gets a 90% efficiency score can reduce 10% of its health inputs while maintaining its health outputs at the same level. In light of Table 2, we see that the efficiency scores are sensible to the DEA model specifications. Indeed, with DEA1 and DEA2 models, we observe an average efficiency score around 80%. It's only 72% with DEA3. With DEA1, 14 countries out of 35 reach a maximum efficiency of 100%. Seven countries are declared efficient with DEA2 and only four countries are found efficient with DEA3 model specification. These declared efficient health systems constitute the frontier or the comparison reference for the other countries' health system. It is noted, however, that only two countries are found efficient regardless of the type of DEA model specification. Both are countries located in Southern Africa, namely Zambia and Zimbabwe.

3.2. The Determinants of the Efficiency Scores of Countries' Health System

The observed efficiency scores reflect not only management errors, but also the environmental factors of each country. In what follows, we will try to establish a relationship between the efficiency scores and a number of structural variables associated with each country.

Table 1. Inputs and outputs of the three different DEA specifications.

	Inputs	Outputs
DEA1	1) Number of doctors per 1000 inhabitants 2) Hospital beds per 1000 inhabitants	1) Life expectancy at birth 2) Mortality rate of children under five
DEA2	1) Number of doctors per 1000 inhabitants 2) Hospital beds per 1000 inhabitants	1) Infant mortality per thousand births
DEA3	1) Health expenditures per capita	1) Life expectancy at birth

Table 2. The efficiency scores.

Countries	Model 1 (DEA1)		Model 2 (DEA2)		Model 3 (DEA3)	
	Scores	Rank	Scores	Rank	Scores	Rank
Benin	1.000	1	0.739	20	0.660	22
Botswana	0.377	35	0.453	32	0.440	33
Burkina Faso	0.834	20	0.799	17	0.796	12
Burundi	0.699	29	0.838	13	0.796	12
Cameroon	0.776	23	0.584	30	0.584	27
Central African Republic	0.600	33	0.755	19	0.727	17
Chad	0.793	22	0.803	16	0.766	15
Comoros	1.000	1	0.463	33	0.462	32
Democratic Republic of Congo	0.639	31	0.648	27	0.645	25
Congo	0.609	32	0.675	25	0.675	20
Côte D'Ivoire	0.715	27	0.869	12	0.842	9
Djibouti	0.725	26	0.827	14	0.827	10
Ethiopia	0.659	30	0.874	11	0.789	14
Gabon	0.818	19	0.637	28	0.637	26
Gambia	0.730	25	0.614	29	0.569	29
Guinea	0.709	28	0.780	18	0.728	18
Guinea Bissau	0.850	18	0.963	10	0.963	6
Kenya	0.499	34	0.579	31	0.576	28
Madagascar	1.000	1	0.712	22	0.682	19
Malawi	0.902	16	1.000	1	1.000	1
Mali	1.000	1	1.000	1	0.911	7
Mauritania	1.000	1	0.710	23	0.669	21
Maurice	1.000	1	0.154	35	0.145	35
Mozambique	0.805	21	1.000	1	1.000	1
Niger	1.000	1	1.000	1	0.898	8
Nigeria	0.739	24	0.671	26	0.652	24
Rwanda	0.867	17	0.983	9	0.981	5
Sao Tome	1.000	1	0.384	34	0.380	34
Senegal	1.000	1	0.725	21	0.550	31
Sudan	1.000	1	0.682	24	0.557	30
Tanzania	0.931	15	0.995	8	0.800	11
Togo	1.000	1	0.811	15	0.658	23
Uganda	1.000	1	1.000	1	0.762	16
Zambia	1.000	1	1.000	1	1.000	1
Zimbabwe	1.000	1	1.000	1	1.000	1
Average score	0.837	-	0.764	-	0.718	-

The literature distinguishes five main categories of factors that could affect inefficiency in the health system of a country ([6] [8] [9] [27]-[29]). These are:

1) Economic variables. These include, among others:

a) The level of economic development as measured by real income per capita calculated assuming purchasing power parity. Indeed, a high income should lead to improved efficiency of the health system. However, it should be noted that the influence of income on health is not as straightforward. It passes through the consumption of goods affecting health (nutrition, hygiene, medical care, education, etc.) The empirical relationship may therefore seem mixed if one also introduces in the regression the variables that characterize the level of consumption of these goods.

b) The extent of poverty and income inequality. Since the poor have limited access to health services, it is expected a positive relationship between inefficiency and the extent of poverty. Similarly, it would be legitimate to think that an unequal income distribution would correspond to a worse health conditions. However, difficult to quantify, the concepts of poverty and inequality are suffering from a lack of universally accepted rigorous definition. Furthermore, there is an abundance of potential indicators for these two related phenomena. As to poverty, because of the lack of satisfactory indicators, either the human poverty index (HPI) or the percentage of the labor force employed in agriculture is used, assuming that the majority of poor are in rural areas. As to inequality in income distributions, the Gini index is often chosen as the relevant explanatory variable.

2) The social and health environment variables. It is assumed that there is a link between the risk of infectious diseases and the quality of the health environment. The frequently used indicators are either the percentage of the population with access to safe water supply or those with access to sanitation services. It is expected a negative correlation between these variables and inefficiency.

3) The parental education. The positive effect of this factor, especially women's education, was emphasized by Caldwell [27]. Indeed, a higher parent education leads to better child nutrition, finer use of health services and greater attention to hygiene. As variables to characterize the instruction, one retains either the literacy rate or the enrollment rate. The most likely hypothesis is that a low level of literacy or schooling is associated with a low efficiency.

4) The demographic variables. In this case, one often uses the density of the population. The expected relationship between this variable and inefficiency is not a priori obvious. For developing countries, particularly in Africa, two other indicators are used: the percentage of the population below 15 years or below five years. The latter is more relevant because the majority of deaths in Africa occur before the age of five years. So there should be a positive relationship between this percentage and inefficiency.

5) The nature of the political regime. According to the UNDP [30], democratic regimes achieve higher health outcomes than dictatorial regimes. One often used variable is the Gastil index of civil liberties and political rights provided by the Freedom House.

Taking into account the availability of data, we estimate the following Tobit model:

$$\text{Ln}(1/\text{EFF}_i) = \alpha_0 + \alpha_1 \text{HPI}_i + \alpha_2 \text{WATER}_i + \alpha_3 \text{EDU}_i + \alpha_4 \text{DENS}_i + \varepsilon_i \quad (6)$$

where, for country i , EFF = DEA efficiency scores. HPI = the UNPD Human Poverty Index. WATER = percentage of the population without access to safe water supply. EDU = the UNPD Education Index. DENS = density of the population.

The results are shown in **Table 3**.

We observe from **Table 3** that the best results, in terms of the significance of the coefficients, are obtained from DEA2 and DEA3 models. Our comments below relate solely to these two models.

We obtain a surprising result with respect to the economic variable used, which is the poverty index (HPI): an inverse relationship between poverty and inefficiency. This somewhat contradictory result is also obtained if we replace HPI by real GDP per capita. Indeed, we found a positive relationship between GDP and inefficiency: it may be possible to spend abundant resources on health while getting very bad results [30]. A more plausible explanation is that the very poor countries are condemned to manage better their health system because they have no other choice. Besides, starting from zero, the relatively limited resources devoted to health can only seem to improve outputs, such as infant mortality.

The health-related variable has the expected sign, but is not significant. The higher is the percentage of the population without access to improved water sources, the greater is the inefficiency.

Table 3. A Tobit model of the determinants of the efficiency scores of countries' health system.

	Model 1 (DEA1)	Model 2 (DEA2)	Model 3 (DEA3)
HPI	-0.076331 (-1.5169)	-0.19393*** (-3.8182)	-0.20802*** (-4.1145)
WATER	-0.034047 (-0.23926)	0.018964 (1.3866)	0.018635 (1.3857)
EDU	-6.1215** (-2.0593)	-7.8596*** (-2.7848)	-9.2490*** (-3.3037)
DENS	-0.0099076 (-0.51426)	0.0033546* (1.8016)	0.0035947* (1.9381)
CONSTANT	6.7812*** (2.0656)	12.023*** (3.7200)	13.753*** (4.1224)

***, **, * represent significant coefficients at the 1%, 5% and 10% level respectively.

Our results confirm the role of education as a determinant of efficiency. Indeed, when the level of education rises, the inefficiency decreases.

Finally, with respect to the demographic variable DENS, we found a positive relationship with the inefficiency. A high density leads to an increased inefficiency.

4. Conclusions

Using published data covering the 1990-1999 period, this paper assessed the efficiency of 35 sub-Saharan countries' health system using the non-parametric technique of DEA. We found that the average efficiency estimates of the countries health system varied from 72% to 84% depending on the combination of inputs and outputs that were considered.

We go beyond this purely descriptive aspect by seeking to identify the factors that can explain the efficiency scores. Our results show that low density of population and the education level contribute to the efficiency of the health system.

To our knowledge, this is one of the first studies using DEA approach to analyzing the efficiency of the health system of countries in sub-Saharan Africa. Additional studies are necessary to understand better and improve the health system of these countries. For example, it would be interesting to extend this study over a longer period. This extension would analyze several sub-periods in order to see the evolution and performance of the health systems. One might also want to make a comparison with other regions. Successful policies of certain countries or regions can inspire others.

References

- [1] Grossman, G. (1972) On the Concept of Health Capital and Demand of Health. *Journal of Political Economy*, **80**, 224-225. <http://dx.doi.org/10.1086/259880>
- [2] Bloom, D. and Canning, D. (2000) The Health and Wealth of Nations. *Science*, **287**, 1207-1209. <http://dx.doi.org/10.1126/science.287.5456.1207>
- [3] Adams, P., Hurd, M.D., McFadden, D.L., Merrill, A. and Ribeiro, T. (2003) Healthy, Wealthy, and Wise? Tests for Direct Causal Paths between Health and Socioeconomic Status. *Journal of Econometrics*, **112**, 3-56. [http://dx.doi.org/10.1016/S0304-4076\(02\)00145-8](http://dx.doi.org/10.1016/S0304-4076(02)00145-8)
- [4] Alsan, M., Bloom, D.E., Canning, D. and Jamison, D. (2007) The Consequences of Population Health for Economic Performance. In: Mills, S., Gibson, L. and Mills, A., Eds., *Health, Economic Development and Household Poverty*, Routledge, Oxford, 21-39. <http://dx.doi.org/10.4324/9780203023570.ch2>
- [5] World Bank (1993) World Development Report: Investing in Health. The World Bank, Washington DC.

- [6] Brunet-Jailly, J. (1998) *Innover dans les Systèmes de Santé: Expériences d'Afrique de l'Ouest*. Edition Karthala, Paris, 435 p.
- [7] Le Gales, C., Buron, C., Costet, N. and Rosman, S. (2001) Développement d'un index d'états de santé pondéré par les utilités en population française: Le Health Utilities Index. *Economie & Prévision*, **150-151**, 71-87. <http://dx.doi.org/10.3406/ecop.2001.6350>
- [8] Brunet-Jailly, J. (1990) *La Pharmacie Populaire du Mali dans le Contexte de l'Initiative de Bamako*. Institut national de recherche en santé publique, Bamako.
- [9] Duret, E. (1999) Décentralisation, Dépenses Publiques et Mortalité Infantile. *Revue d'Economie du Développement*, **4**, 39-68.
- [10] WHO (2000) *The World Health Report: Health System: Improving Performance*. Genève.
- [11] Brilleau, A. (2004) Les indicateurs Liés à la Mise en Œuvre des Cadres Stratégiques de Lutte contre la Pauvreté. *Stateco*, **98**, 51-72.
- [12] Bosman, N. and Fecher, F. (1992) Une Étude Comparative de l'Efficacité Technique du Secteur de la Santé au Sein des Pays de l'OCDE. Université de Liège, Liège, CIRIEC, Working Paper 92/08.
- [13] Leleu, H. and Derveux, B. (1997) Comparaison des Différentes Mesures d'Efficacité Technique: Une Application aux Centres Hospitaliers Français. *Économie & Prévision*, **129**, 101-119. <http://dx.doi.org/10.3406/ecop.1997.5866>
- [14] Plane, P. (1997) Efficience Technique et Développement. Introduction. *Revue d'Economie du Développement*, **3**, 3-7.
- [15] El Asraoui, H., Boussemart, J.P. and Lesourd, J.B. (1999) Rentabilité des Cultures Énergétiques et Frontières d'Efficacité. (Badillo, P.Y. and Paradi, J.C., Eds.)
- [16] Banker, R.D., Conrad, R. and Strauss, R. (1986) A Comparative Application of Data Envelopment Analysis and Translog Methods: An Illustrative Study of Hospital Production. *Management Science*, **32**, 30-44. <http://dx.doi.org/10.1287/mnsc.32.1.30>
- [17] Grosskopf, S. and Valdmanis, V. (1987) Measuring Hospital Performance: A Non-Parametric Approach. *Journal of Health Economics*, **6**, 89-107. [http://dx.doi.org/10.1016/0167-6296\(87\)90001-4](http://dx.doi.org/10.1016/0167-6296(87)90001-4)
- [18] Färe, R., Grosskopf, S. and Valdmanis, V. (1989) Capacity, Competition and Efficiency in Hospitals: A Nonparametric Approach. *Journal of Productivity Analysis*, **1**, 123-138. <http://dx.doi.org/10.1007/BF00157792>
- [19] Chilingirian, J.A. (1994) Exploring Why Some Physicians' Hospital Practices Are More Efficient: Taking DEA inside the Hospital. In: Charnes, A., Cooper, W.W., Lewin, A. and Seiford, L., Eds., *Data Envelopment Analysis: Theory, Methodology, and Applications*, Kluwer Press, Norwell, 167-193. http://dx.doi.org/10.1007/978-94-011-0637-5_9
- [20] Charnes, A., Cooper, W.W. and Rhodes, E. (1978) Measuring the Efficiency of Decision Making Units. *European Journal of Operational Research*, **2**, 429-444. [http://dx.doi.org/10.1016/0377-2217\(78\)90138-8](http://dx.doi.org/10.1016/0377-2217(78)90138-8)
- [21] Zhu, J. (2002) *Quantitative Models for Performance Evaluation and Benchmarking: Data Envelopment Analysis with Spreadsheets and DEA Excel Solver*. International Series in Operations Research and Management Science, Vol. 51, Springer, Berlin.
- [22] Sedzro, K. and Keita, M. (2009) Assessing the Efficiency of Microfinance Institutions Using Data Envelopment Analysis. *Journal of International Finance & Economics*, **9**, 54-67.
- [23] World Bank (2002) *African Development Indicators*. The World Bank, Washington.
- [24] Hoff, A. (2007) Second Stage DEA: Comparison of Approaches for Modelling the DEA Score. *European Journal of Operational Research*, **181**, 425-435. <http://dx.doi.org/10.1016/j.ejor.2006.05.019>
- [25] Sueyoshi, T., Goto, M. and Omi, Y. (2010) Corporate Governance and Firm Performance: Evidence from Japanese Manufacturing Industries after the Lost Decade. *European Journal of Operational Research*, **203**, 724-736. <http://dx.doi.org/10.1016/j.ejor.2009.09.021>
- [26] Coelli, T. (1996) *A Guide to DEAP Version 2.1: A Data Envelopment Analysis (Computer) Program*. CEPA Working Paper 96/08.
- [27] Flegg, A.T. (1982) Inequality of Income, Illiteracy and Medical Care as Determinants of Infant Mortality in Underdeveloped Countries. *Population Studies*, **36**, 441-458. <http://dx.doi.org/10.1080/00324728.1982.10405597>
- [28] Flegg, A.T. (1983) On the Determinants of Infant Mortality in Underdeveloped Countries. *International Journal of Social Economics*, **10**, 38-51. <http://dx.doi.org/10.1108/eb013943>
- [29] Brun, J.F. and Mathonat, J. (1997) Les Effets du Financement Extérieur sur le Niveau des Dépenses Publiques d'Éducation et de Santé dans les Pays en Voie de Développement. Une Analyse Économétrique sur Données de Panel. CERDI, Etudes et documents E.97.15.
- [30] United Nations Development Program (1993) *Human Development Reports*. Oxford University Press, New York.

Evaluation Indexes of Degree of Closeness between Strategy and Project Portfolio Allocation

Libiao Bai, Sijun Bai

School of Management, Northwestern Polytechnical University, Xi'an, China
Email: hanshannuanyang@163.com, baisj@huading.net.cn

Received 19 November 2014; accepted 3 December 2014; published 13 January 2015

Copyright © 2015 by authors and Scientific Research Publishing Inc.
This work is licensed under the Creative Commons Attribution International License (CC BY).
<http://creativecommons.org/licenses/by/4.0/>



Open Access

Abstract

The main activities in project portfolio allocation management are selecting the right project components given a strategy. It is crucial to establish a scientific system of evaluation indexes to guarantee the closeness between strategy and project portfolio allocation optimally. With organizations growing in sizes, the functions and objectives of project components are becoming more and more different. It is necessary to set evaluation indexes of the degree of closeness from the perspectives of financial, market share, social effects, and so on according to the strategy-oriented process of project portfolio allocation. This paper proposes a project portfolio allocation process under strategic orientation and evaluation indexes of the degree of closeness between strategy and project portfolio allocation. This will help projects managers make portfolio allocation decisions.

Keywords

Project Portfolio Allocation, Evaluation Indexes, Degree of Closeness, PPA Process

1. Introduction

In the information era, with the growing competition in the market, project portfolio management (PPM) has become an effective means to enhance the competitiveness of enterprises. In particular, project portfolio allocation (PPA) has been given more and more attention from industry experts and academic scholars because it can effectively help implement an organization's strategy.

PPA problems typically consist of resources allocation and schedule optimization. Many works emphasize the importance of resource allocation. The resources allocation problem is dynamic which should solve the large

scale instances for a variety of resource allocation problems when we try to develop optimization models [1]. [2] considers the problem of multi-project resource allocation as a multi-channel queuing system and use language like GPSS to solve this problem. As same as the traditional projects, the resources allocation problem is also one of the most important problems in software project portfolios, and the systematic approach called the Best-Fitted Resource (BFR) methodology which considers complete skill sets of candidates can assign resources to tasks effectively [3]. In a multi-project matrix environment, the conflicts of resource allocation occur not only among different projects, but also among different activities even from the same project. A corporation will achieve higher organizational performance only if all of managers agree upon the resource allocation policy and try their best to implement it [4].

As one of the most important aspects of PPA problem, project scheduling for project portfolio management becomes more significant than ever before. Many scholars have thoroughly studied the project scheduling problem. Many of those models have been built to optimize this problem considering the scheduling process for a specific period only or at period one [5]-[7]. [8] addresses multi-project scheduling in a critical chain problem. In this paper, a multi-objective optimization model has been proposed and used to generate alternative schedules based on the importance of different projects and objectives [8]. Many other models are proposed to present the relationship between resources allocation and schedule optimization, which try to find the most optimal approach for solving the resource-constrained project scheduling problem [9]-[11]. The resource-constrained project scheduling problem (RCPSP) with a fixed date for every activity has the objective to complete the task in quality within the established deadline [12]. In the resource-constrained project scheduling problem, it is required to restart a fixed setup time while an activity is began, all of activities are interrelated by finish to start type precedence relations with the time lag of the minimum [13]. In order to effectively tackle the resource-constrained project scheduling problem, two alternative approaches, FLP and PABC, have been proposed and applied into measure the relationship between resource and project scheduling, also the effectiveness of these approaches for RCPSP are showed by a series of computational experiments [14].

We can see the followings from the existing literature. The studies on the topics of PPA, including resources allocation, schedule optimization and RCPSP, have made great contributions to enhance organizational competitiveness, but they have rarely analyzed the evaluation indexes. As a result, the degree of closeness strategy and PPA cannot be scientifically measured. In this paper, we will propose a process model to analyze the relationship between strategy and PPA firstly. Then we will try to propose a system of evaluation indexes of the degree of closeness on the basis of the process model.

This paper is structured as follows. We propose a process model for PPA in Section 2. In Section 3 we will propose the system of evaluation indexes of the degree of closeness. The final section provides the conclusions.

2. PPA Process Based on the Degree of Closeness to Strategy

This section introduces the traditional PPA process firstly. In order to combine with organizational strategy, this section also puts forward a PPA process based on its degree of closeness to strategy.

2.1. Traditional PPA Process

The process of traditional PPA is divided into four stages: concept, feasibility study, selection and implementation [15], which is shown in **Figure 1**:

1) Concept stage of PPA

In this stage, the main work is to prepare project proposals, which will analyze the necessity of the project to be implemented. In order to prepare project proposals, the market analysts, technicians and manager should analyze the impact of the project being implemented on other ongoing projects.

2) Feasibility study stage of PPA

Organization's situation and strategic objectives, analysis the superiority of the proposed projects in the first stage from the aspects of risk/benefit, the project capacity (e.g., implementation capacity, financial capacity, technical capacity, management capacity), and technical superiority and competitive barriers will provide a reference to select the components of PPA.

3) Component selection stage of PPA

Based on the result of feasibility study in the second stage, all project components and configured tentatively. Previous project experience describing the degree of closeness between project components and organization's

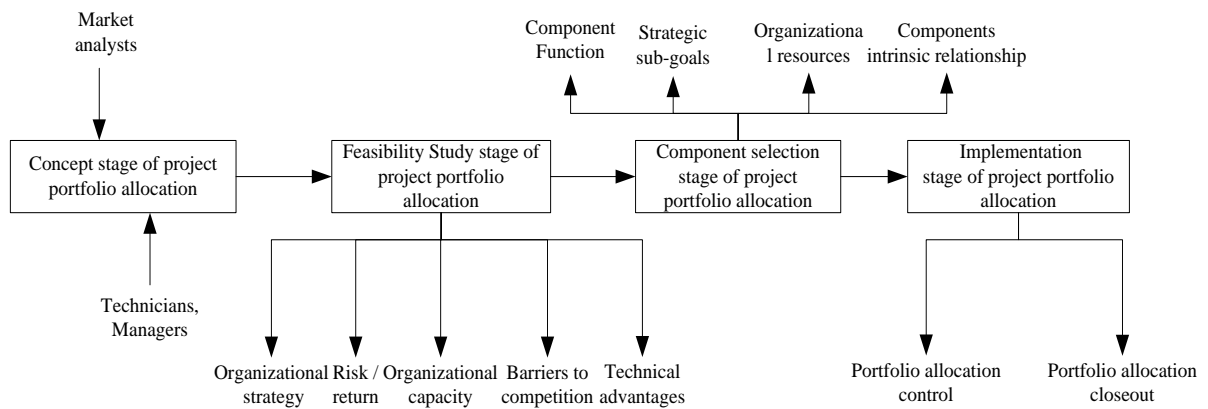


Figure 1. Four stages of traditional PPA.

strategic objectives are utilized. The best project components are selected and a trial allocation is formed. The most important work in this stage is to make sure the trial allocation meets organizational resource constraints and internal relationships among components.

4) Implementation stage of PPA

Implementation stage is the main part of PPA, including portfolio allocation implementation, allocation adjustment and optimization. How to allocate the components? How to implement the priority components and how to implement the component issues? These are the key issues in this stage. With these issues, organizers analyze variations and the reasons for them in the process of implementation, develop and implement appropriate corrective measures to optimize the allocation of portfolio solutions to ensure the PPA is aligned with the organization’s strategy during the process of project portfolio implementation.

2.2. PPA Process Based on the Degree of Closeness to Strategy

The biggest difference between the PPA process based on the degree of closeness to strategy and traditional PPA process is the former takes into account the organization’s strategic influence on portfolio, which subdivides organization strategy in details and makes it loaded with each project to be implemented. Therefore, a reasonable PPA process would become the primary guarantee that the organization’s strategic objectives are to be achieved.

In this section, organization strategy will be decomposed to optimize traditional project portfolio process. On this basis, the process of PPA for the degree of closeness to strategy has been proposed, which is shown in **Figure 2**.

In **Figure 2**, the strategic target has been divided into two major parts: the financial and the non-financial strategic targets. The PPA process based on the degree of closeness to strategy is as below.

1) Build the collection of alternative projects

The collection of alternative projects is based on the need of the development of enterprises. Managers collect, collate, analyze and improve the information on the projects which will likely bring new opportunities for organizational development, generate synergies among projects in terms of costs, expected returns, client satisfaction, risk, organizational conditions, internal human resources, hardware and software. Managers also analyze the state of the implemented project components, put the projects which meet the organization’s strategic objectives and development needs into a same collection, and build a “project pool” under the guidance of the strategy.

2) Alternative project evaluation

The steps for detailed implementation in this stage are as follows.

a) Collect the information on the projects to be implemented: analyze the possibility of projects by collecting and organizing the information and data.

b) Evaluate the projects to be implemented: evaluate the projects from the aspects of financial, non-financial and the degree of closeness to strategy, group the projects which meet financial and non-financial constraints into a “project pool”. For those projects which cannot meet financial and non-financial constraints but meet the strategic needs, they can also be grouped into the “project pool” to ensure the PPA is close to strategy. All other remaining projects are then removed.

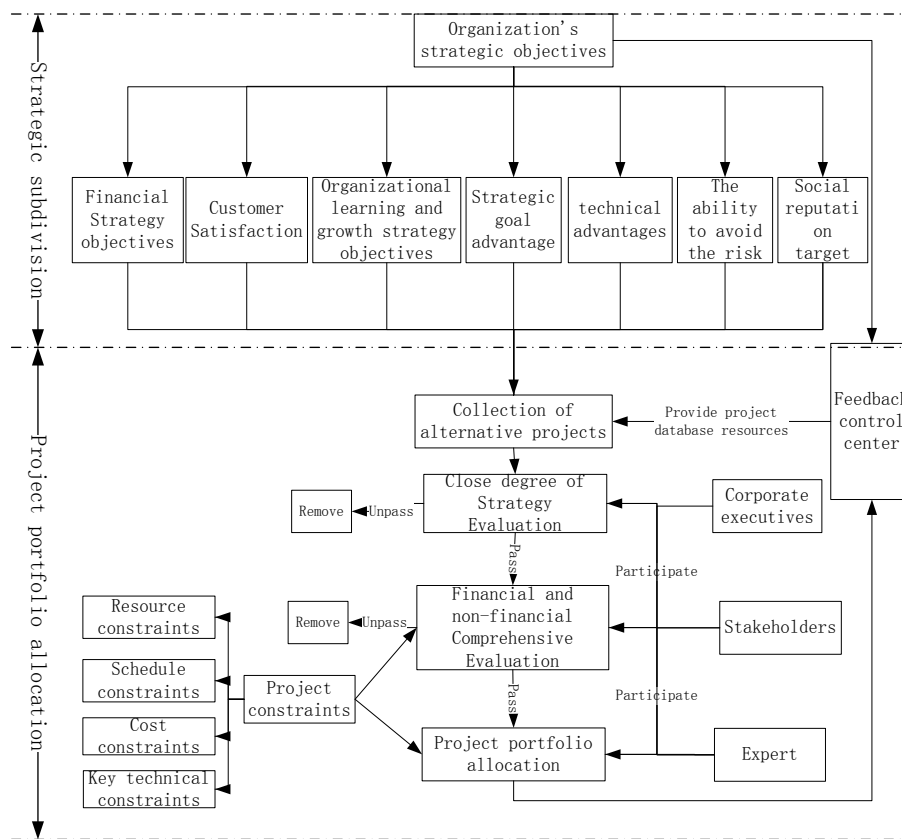


Figure 2. PPA process based on the degree of closeness to strategy.

3) Project portfolio allocation

The ultimate goal of PPA models is to ensure all the project components to be implemented can achieve the best selection and the optimal allocation in the organization. Senior management, experts and stakeholders participate in project evaluation and feasibility studies at this stage of PPA selection to make sure the components bearing the organization's strategy effectively. At the same time, meta-analysis and feedback of the portfolio allocation process are used to enrich and complement the content of project information database, which will support the next stage of PPA.

2.3. The Advantages of the PPA Process Based on the Degree of Closeness to Strategy

Traditional division of portfolio allocation process is based on the PPA's implementation phase, which overemphasizes the evaluation of project portfolio components. However, it does not take strategy into account causing the process to deviate from the strategy. Due to the lack of scientific management allocation tools and process implementation guidance, most organizations still use the single project management approach to managing the portfolio allocation. It will bring a strong randomness in the process of project portfolio selection and portfolio allocation in this kind of management pattern. This is a very important flaw. Consequently, the managers cannot allocate the resources at the level of organization's strategic objectives. The PPA process based on the degree of closeness is designed to solve this problem. This process is based on the decomposition of the strategic objectives effectively which means each allocation component is able to undertake a sub-strategic objective and realize the organization strategy effectively. Meanwhile, this process can combine with organizational changes and the competition of market environment and dynamically adjust the allocation component so that it can keep a high degree of closeness to strategy.

Compared with traditional allocation process, the advantage of PPA process based on the degree of closeness is that it has created a virtuous cycle between strategy and project portfolio management, which help achieve the organization strategy by project management. Through the layers of tissue segmentation strategy, building stra-

tegic objectives at different levels (enterprise level, portfolio level, functional level) to achieve a level of commitment to the strategic objectives division project components; at the same time, in the implementation of the project portfolio allocation process, strategic organizational layers of sub-goals for project implementation can be achieved in accordance with the organization during the project portfolio allocation strategies for the implementation of the management objective dynamic control, ensuring strategic goal of optimization. Therefore, based on the portfolio strategy nearness of the configuration process presented in this chapter with respect to the traditional configuration process, the organization in achieving strategic objectives, to ensure that organizations achieve upgrade cycle has a huge advantage and reasonable. Therefore, the process of PPA built in this section has enormous advantages in achieving the sustainable development of organization.

3. Evaluation Indexes System for the Degree of Closeness between Strategy and PPA

3.1. Principles of Building the System of Evaluation Indexes of the Degree of Closeness

In order to ensure the validity of the index system, we should follow the following principles.

1) Dynamic

This index system should be able to dynamically adjust with the organization strategy adjustment. The weight of each index should follow strategic changes, so that it can dynamically and scientifically reflect the relationship between portfolio allocation component and strategy.

2) Systematic

In order to ensure the index system is scientific and systematic, we should make a comprehensive analysis of the internal relations among various factors during the process of building the index system. This means the index system should try to achieve the system-wide optimization.

3) Comparability

This evaluation index system is for all organizations and all project components. Therefore, it must be across various types of enterprises to achieve the quantitative comparison.

4) Relative independence

This principle means each index in this system should keep independent to prevent redundancy.

3.2. Construction of the System of Evaluation Index for the Degree of Closeness

As **Figure 2** shows, the strategic target has been divided into financial and non-financial strategic targets. Financial objectives are mainly used to measure the progress of achieving strategic objectives and are familiar to managers. However, using the financial indexes only is insufficient. It is necessary to use non-financial indexes for auxiliary measurement and calculation. There are lots of non-financial indexes used to measure the degree organization's strategic objectives achieved. We can group the non-financial indexes into six categories [16]: customer satisfaction, strategic goals advantage, organizational growth, technical superiority target formation, risk avoidance capability and social reputation. On the basis of these categories, this paper incorporates strategy into the area of evaluation indexes. Subdividing the non-financial indexes into this sub-index according to the management indexes by Standardization Project Management Institute [17], we obtain the system of evaluation indexes of the degree of closeness between strategy and PPA, as shown in **Table 1**.

3.3. Optimization of Evaluation Indexes of the Degree of Closeness between Strategy and PPA

In the Section 3.2, this paper has initially constructed evaluation indexes system for the degree of closeness between strategy and PPA from the aspects of financial index, customer satisfaction, strategic objectives, organization growth, the advantage of technical advantages, the ability to avoid the risk and social reputation. However, this index system is based on the improvement of the existing literature and its scientific validity cannot be guaranteed. To solve this problem, it is necessary to optimize the index system. In this paper we invited 10 experts in the area of project management form the PMRC (Project Management Research Committee). We use the expert assessment method to achieve optimal allocation index system of strategy upgrade. The process of this optimization is shown as below.

1) Sort out the evaluation indexes of the degree of closeness which need to be studied, then distribute the

Table 1. Evaluation indexes of the degree of closeness between strategy and project portfolio allocation.

Financial Indexes	NPV	
	Return on investment	
	Payback period	
	Capital turnover	
	Financing methods	
	Inventory turnover	
	Profit rate	
	Customer satisfaction	Technical superiority target formation
	1) Customer relationship evaluation value for strategic results; 2) The strategic results to customers effects; 3) The degree of satisfaction of customer expectations; 4) Customer loyalty; 5) Lost customer return rate.	1) Technology leadership degree; 2) Architecture consistency; 3) The adoption of new technology achievements; 4) The technology can be solid; 5) The technical maturity and reliability; 6) A number of patents and property rights.
	Strategic goals advantage	Risk avoidance capability
n-financial indexes	1) Fitness of strategic objectives and business development; 2) The degree of strategic objectives can be broken down; 3) The image of the product enhanced; 4) The degree of corporate reputation enhanced; 5) The competitiveness of the enterprise market enhanced.	1) Identification of risk factors complete degree; 2) A reasonable degree of risk to the organization; 3) Timeliness and effectiveness of risk measures; 4) The risk of handling scientific; 5) The accuracy of risk prediction.
	Organizational growth	Social reputation
	1) Professional training capability; 2) Employee satisfaction; 3) Enhance organizational project management maturity; 4) The members of the organization to enhance collaboration capabilities earnings; 5) Integration and sharing of resources to bring; 6) The optimization of the management process.	1) The degree of organization of social responsibility; 2) The organization of social appeal; 3) Good public relations degree; 4) QOS reputation; 5) The social image recognition; 6) The preference of product for the customer.

evaluation forms to invited experts, ask them to sort all indexes in this system according to the importance, ranging from 1 to 10. If the experts believe that there is a need to add or delete an indicator, they can also state that. The basic format of the table is shown in **Table 2**:

2) Recycle and sort out the experts' advice, set the weight of experts' advice according to the reputation of the experts in the area of this research, management experience and their published literature. This paper only takes the financial indexes as an example to analyze the experts' advice due to page limit. The summarization of expert's opinions on financial evaluation indexes of the degree of closeness between strategy and project portfolio allocation is shown in **Table 3**:

3) Comprehensive value of evaluation indexes of the degree of closeness between strategy and PPA

According to **Table 3**, we can calculate the comprehensive evaluation value of each sub-index by using the weight sum method. If the comprehensive evaluation value $V_{I_n} < 5$, which means the index I_n has little effect on the strategic and portfolio allocation, then I_n will be deleted from the system of evaluation indexes. Take the NPV as a case, it is easy to calculate the comprehensive value V_{I_1} :

$$\begin{aligned}
 V_{I_1} &= 0.08 \times 9 + 0.12 \times 7 + 0.15 \times 5 + 0.05 \times 3 + 0.09 \times 8 + 0.13 \times 7 + 0.08 \times 6 + 0.15 \times 9 + 0.09 \times 8 + 0.06 \times 4 \\
 &= 6.27
 \end{aligned}$$

Similarly, we can get the comprehensive evaluation value of other indexes. The results are shown in **Table 3**.

4) Index optimization

Table 2. Table of consultation for evaluation indexes.

Indexes	I_1	I_2	I_3	I_n
Evaluation value					
Other comments					

Note: I_n represents the n th index to be optimized in the evaluation indexes system.

Table 3. Summarization of expert’s opinions on financial evaluation indexes of the degree of closeness between strategy and PPA.

Expert weight	Index	NPV I_1	return on investment I_2	payback period I_3	capital turnover I_4	Financing methods I_5	Inventory turnover I_6	Profitrate I_7
0.08		9	6	5	4	6	5	8
0.12		7	6	9	7	8	6	7
0.15		5	5	7	6	6	7	8
0.05		3	4	7	2	8	5	6
0.09		8	6	3	5	5	4	5
0.13		7	5	8	4	8	3	6
0.08		6	6	9	8	8	7	8
0.15		9	5	7	9	9	6	7
0.09		8	4	3	5	8	5	6
0.06		4	5	9	6	6	3	5
Comprehensive value V_{I_n}		6.27	4.9	6.22	4.82	6.82	4.72	6.33

As shown in **Table 3**, the comprehensive evaluation values of other indexes are 6.27, 4.9, 6.22, 4.82, 6.82, 4.72, 6.33. We delete the indexes with the comprehensive value less than 5. We then can obtain the new financial evaluation indexes of the degree of closeness between strategy and PPA: financing methods, payback period, return on investment, profit rate. Using the same approach, we can obtain results of evaluation indexes of the degree of closeness between strategy and PPA after optimization. This is shown in **Figure 3**.

4. Conclusion

According to the project portfolio allocation process under strategic orientation, this paper proposes a PPA process for the degree of closeness based on the introduction of traditional PPA process. In order to ensure the scientific validity of the index system, we introduce the principles for building the system of evaluation indexes, then tentatively construct the system of evaluation indexes of the degree of closeness between strategy and PPA from the aspects of financial index, customer satisfaction, strategic objectives, organization growth, the advantage of technical advantages, the ability to avoid the risk and social reputation. However, this index system is based on the improvement of the existing literature, so its scientific validity cannot be guaranteed. In order to solve this problem, this paper employs optimization. Finally, this paper proposes a new system of evaluation indexes of the degree of closeness between strategy and PPA. This new system has enormous advantages in achieving the sustainable development of organizations. In short, the system of evaluation indexes proposed in this paper not only rectifies the weaknesses and deficiencies in previous studies of PPA, but also makes a great contribution to helping the manager find the best project portfolio allocation from the set of projects to be implemented.

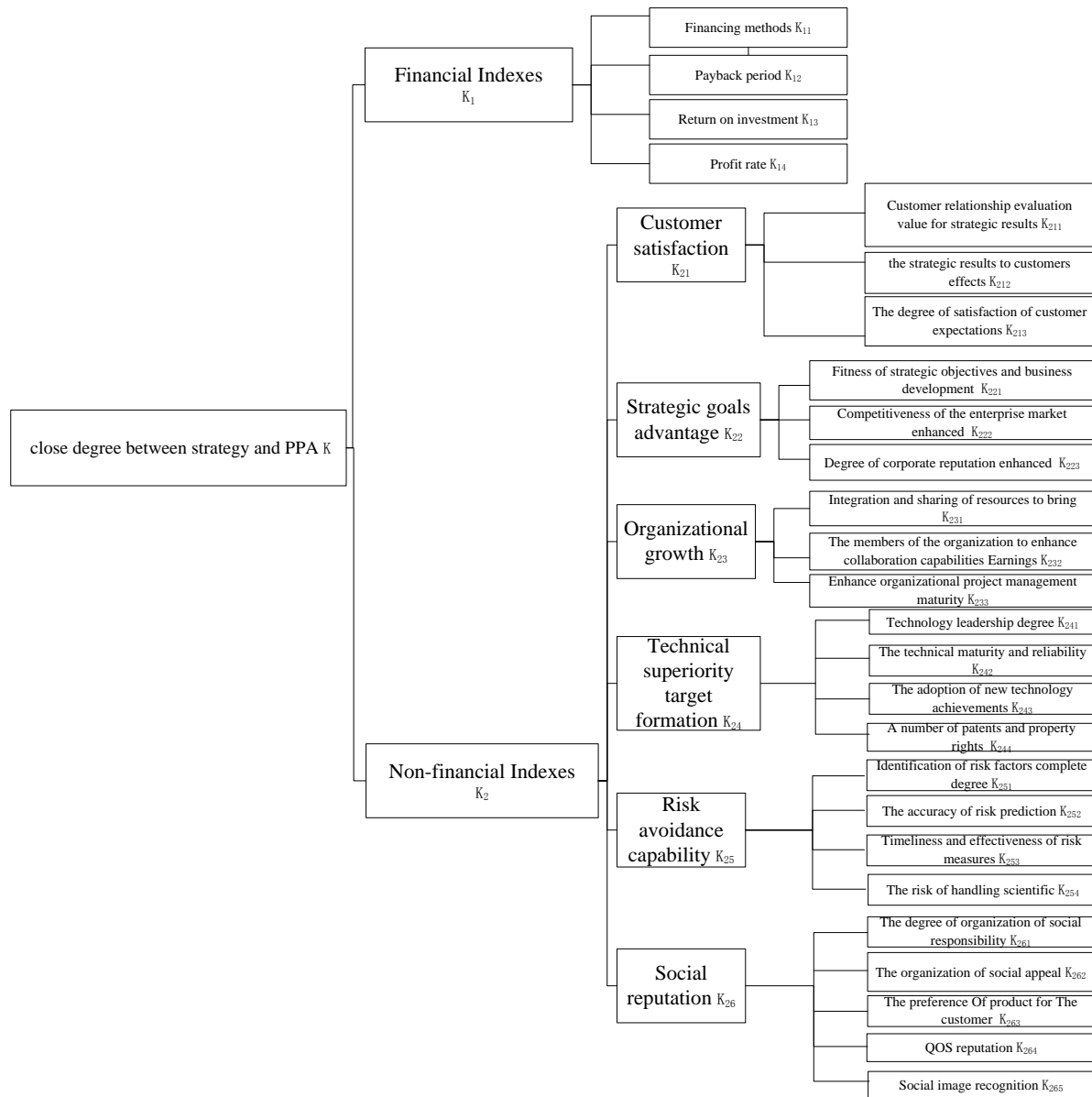


Figure 3. The system of evaluation indexes of the degree of closeness between strategy and PPA after optimization.

Acknowledgements

This study is sponsored by National Natural Science Foundation of China under Grant No.7117212 and Aviation Science Fund of China under Grant No. 2012ZG53083.

References

- [1] Bertsimas, D., Gupta, S. and Lulli, G. (2014) Dynamic Resource Allocation: A Flexible and Tractable Modeling Framework. *European Journal of Operational Research*, **236**, 14-26. <http://dx.doi.org/10.1016/j.ejor.2013.10.063>
- [2] Fatemi Ghomi, S.M.T. and Ashjari, B. (2002) A Simulation Model for Multi-Project Resource Allocation. *International Journal of Project Management*, **20**, 127-130. [http://dx.doi.org/10.1016/S0263-7863\(00\)00038-7](http://dx.doi.org/10.1016/S0263-7863(00)00038-7)
- [3] Otero, L.D., Centeno, G., Ruiz-Torres, A.J., et al. (2009) A Systematic Approach for Resource Allocation in Software Projects. *Computers & Industrial Engineering*, **56**, 1333-1339. <http://dx.doi.org/10.1016/j.cie.2008.08.002>
- [4] Laslo, Z. and Goldberg, A.I. (2008) Resource Allocation under Uncertainty in a Multi-Project Matrix Environment: Is

- Organizational Conflict Inevitable? *International Journal of Project Management*, **26**, 773-788.
<http://dx.doi.org/10.1016/j.ijproman.2007.10.003>
- [5] Gonçalves, J.F., Mendes, J.J.M. and Resende, M.G.C. (2008) A Genetic Algorithm for the Resource Constrained Multi-Project Scheduling Problem. *European Journal of Operational Research*, **189**, 1171-1190.
<http://dx.doi.org/10.1016/j.ejor.2006.06.074>
- [6] Huang, W., Ding, L., Wen, B., *et al.* (2009) Project Scheduling Problem for Software Development with Random Fuzzy Activity Duration Times. Springer, Berlin, Heidelberg, 60-69.
- [7] Ke, H. and Liu, B. (2010) Fuzzy Project Scheduling Problem and Its Hybrid Intelligent Algorithm. *Applied Mathematical Modelling*, **34**, 301-308. <http://dx.doi.org/10.1016/j.apm.2009.04.011>
- [8] Wang, W., Wang, X., Ge, X., *et al.* (2014) Multi-Objective Optimization Model for Multi-Project Scheduling on Critical Chain. *Advances in Engineering Software*, **68**, 33-39. <http://dx.doi.org/10.1016/j.advengsoft.2013.11.004>
- [9] Majazi Dalfard, V. and Ranjbar, V. (2012) Multi-Projects Scheduling with Resource Constraints & Priority Rules by the Use of Simulated Annealing Algorithm. *Tehnički Vjesnik*, **19**, 493-499.
- [10] Zheng, Z., Shumin, L., Ze, G., *et al.* (2013) Resource-Constraint Multi-Project Scheduling with Priorities and Uncertain Activity Durations. *International Journal of Computational Intelligence Systems*, **6**, 530-547.
<http://dx.doi.org/10.1080/18756891.2013.789152>
- [11] Singh, A. (2014) Resource Constrained Multi-project Scheduling with Priority Rules & Analytic Hierarchy Process. *Procedia Engineering*, **69**, 725-734. <http://dx.doi.org/10.1016/j.proeng.2014.03.048>
- [12] Khoshjahan, Y., Najafi, A.A. and Afshar-Nadjafi, B. (2013) Resource Constrained Project Scheduling Problem with Discounted Earliness-Tardiness Penalties: Mathematical Modeling and Solving Procedure. *Computers & Industrial Engineering*, **66**, 293-300. <http://dx.doi.org/10.1016/j.cie.2013.06.017>
- [13] Afshar-Nadjafi, B. and Majlesi, M. (2014) Resource Constrained Project Scheduling Problem with Setup Times after Preemptive Processes. *Computers & Chemical Engineering*, **69**, 16-25.
<http://dx.doi.org/10.1016/j.compchemeng.2014.06.012>
- [14] Jia, Q. and Seo, Y. (2013) Solving Resource-Constrained Project Scheduling Problems: Conceptual Validation of FLP Formulation and Efficient Permutation-Based ABC Computation. *Computers & Operations Research*, **40**, 2037-2050.
<http://dx.doi.org/10.1016/j.cor.2013.02.012>
- [15] Zhong, W.J. (2009) Theory and Methods for Enterprise Technology Innovation Management. Science Press, Beijing, 118-119.
- [16] Du, X., Sun, S. and Ou, L. (2006) A Multi-Phase Framework of R&D Project Balanced Portfolio Selection. *Science of Science and Management of S & T*, **11**, 006.
- [17] The Project Management Institute, Inc. (2004) A Guide to the Project Management Body of Knowledge. 3rd Edition, Vol. 11, Project Management Institute, Inc., Newtown Square, 245.



American Journal of Operations Research

ISSN 2160-8830 (Print) ISSN 2160-8849 (Online)

<http://www.scirp.org/journal/ajor>

AJOR is an international scientific journal dedicated to the publication and public discussion of high quality, original papers that contribute to the methodology of operational research and to the practice of decision making.

Editor in Chief

Prof. Jinfeng Yue

Middle Tennessee State University, USA

Editorial Board

Dr. Javier De Andrés
Prof. Janine E. Aronson
Dr. Annamaria Barbagallo
Dr. Nabil Belacel
Prof. Ignacio Castillo
Prof. Xu Chen
Prof. Muhammad El-Taha
Prof. Carmen Galé
Prof. Xianghua Gan
Prof. Xiuli He
Prof. Mhand Hifi
Prof. Zhimin Huang
Prof. Zhibin Jiang

Prof. Ricardo Josa-Fombellida
Prof. Dennis Leech
Prof. Deng-Feng Li
Prof. Liang Liang
Dr. Pedro Lorca
Prof. Charles L. Munson
Dr. Jamal Ouenniche
Prof. Joaquin Antonio Pacheco Bonrosto
Prof. Javier Ramirez Rodriguez
Prof. Bhaba R. Sarker
Prof. Renduchintala Raghavendra Kumar Sharma
Dr. Chunming (Victor) Shi
Prof. Andranik Tangian

Prof. Etsuji Tomita
Dr. Delfim F. M. Torres
Prof. Evangelos Triantaphyllou
Dr. Manish Verma
Dr. Yu Amy Xia
Prof. Yi-Min Xie
Dr. Shenghan Xu
Dr. Jiping Yang
Dr. Shilei Yang
Prof. Peng-Yeng Yin
Dr. Xiaohang Yue

Subject Coverage

This journal invites original research and review papers that address the following issues in operations research. Topics of interest include, but are not limited to:

1. Operations Research and Optimization Theory and Research Technical Approaches

Computational Intelligence and Information Management
Continuous Optimization
Decision Support Systems, Multi-Criteria Decision Methods
Discrete Optimization
Expert Systems
Heuristics Mathematical Programming
Networks
Queues
Simulation
Stochastic Models and Statistics
Time Series Analysis

2. Manufacturing and Service Operations Research

Forecasting
Inventory
Location
Logistics, Transportation Warehousing and Maintenance
Planning and Scheduling
Product and Service Design

Project Management
Quality Management
Revenue Management
Supply Chain Management

3. Interfaces with Other Disciplines

Community Operations Research
Complex Systems
Education Operations Research
Environmental and Energy Issues
Financial Engineering
Government Operations Research
Health Services Operations Research
Marketing Science
Military and Homeland Security
Operations Research in Nonprofit Organization
Policy Modeling and Public Sector OR
Productivity and Efficiency in the Public Sector
Sports Operations Research
Telecommunications and Networking

We are also interested in short papers (letters) that clearly address a specific problem, and short survey or position papers that sketch the results or problems on a specific topic. Authors of selected short papers would be invited to write a regular paper on the same topic for future issues of the AJOR.

Notes for Intending Authors

Submitted papers should not have been previously published nor be currently under consideration for publication elsewhere. Paper submission will be handled electronically through the website. All papers are refereed through a peer review process. For more details about the submissions, please access the website.

Website and E-mail

<http://www.scirp.org/journal/ajor>

E-mail: ajor@scirp.org

What is SCIRP?

Scientific Research Publishing (SCIRP) is one of the largest Open Access journal publishers. It is currently publishing more than 200 open access, online, peer-reviewed journals covering a wide range of academic disciplines. SCIRP serves the worldwide academic communities and contributes to the progress and application of science with its publication.

What is Open Access?

All original research papers published by SCIRP are made freely and permanently accessible online immediately upon publication. To be able to provide open access journals, SCIRP defrays operation costs from authors and subscription charges only for its printed version. Open access publishing allows an immediate, worldwide, barrier-free, open access to the full text of research papers, which is in the best interests of the scientific community.

- High visibility for maximum global exposure with open access publishing model
- Rigorous peer review of research papers
- Prompt faster publication with less cost
- Guaranteed targeted, multidisciplinary audience



**Scientific
Research
Publishing**

Website: <http://www.scirp.org>

Subscription: sub@scirp.org

Advertisement: service@scirp.org