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북극항로 무역 성장을 위한 러시아 북극의 항만 효율화에 관한 연구*

A Study on Port Efficiency in the Russian Arctic as a Key Factor for Trade Growth in the Northern Sea Route

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| 목 차 |

국문초록

북극 해빙의 급속한 용해는 유럽과 아시아 사이의 실행 가능한 대체 해로로서 북극항로에 대한 관심을 증대시켜 왔다. 현재까지 북극항로의 기술적 실현 가능성, 안전성, 수익성, 환경 영향 등을 고려한 광범위한 연구가 진행되어 왔다. 북극항로는 국제 교역의 중요한 루트가 될 것이며, 무역 원활화를 위해서는 항만 효율성이 무엇보다 중요하다. 그럼에도 불구하고 북극항로의 중요한 위치해 있는 항만들, 특히 러시아 북극 항만들의 효율성 평가에 대한 연구가 제한적인 상황이다. 따라서 본 연구는 데이터 포락 분석(DEA) 모델과 Malmquist 생산성 지수를 적용하여 러시아 17개 항구의 운영 현황을 분석하고, 효율성을 평가하고자 한다. DEA 분석 결과, 주로 서부 지역에 속하는 항만들의 효율성이 높게 나타났으며, 특히 무르만스크와 바란데이와 같은 항구는 지속적으로 높은 효율성과 꾸준한 규모의 수익을 보여주고 있음이 규명되었다. DEA-Malmquist 모형 결과에 의하면 기술 발전에도 불구하고 모든 항구에 대한 전반적인 자원 활용 효율성의 개선 정도가 상대적으로 적은 것으로 나타났다. 본 연구의 결과는 인프라 개발 계획 및 관련 정책 수립을 위한 기초자료를 제공하고, 북극항로 항만 당국에 실질적인 시사점을 제공한다.

〈주제어〉 Port efficiency, Northern Sea Route, Russian Arctic, DEA, Malmquist Productivity Index Trade strategies

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Ⅰ. Introduction

The Northern Sea Route (NSR) is a shipping route that stretches along the Arctic coast of Russia. It extends from the Novaya Zemlya archipelago in the west to the Bering Strait in the east. It is part of the larger Northeast Passage, which encompasses various waterways and straits in the Arctic region (see Figure 1).

Due to the ongoing reduction of Arctic sea ice the route is gradually becoming more navigable for commercial shipping (AMAP,2021). Inevitably, its potential as a shortcut between Europe and Asia, offering substantial reductions in transit times compared to traditional southern routes like the Suez Canal, has captured the interest of the shipping industry. However, despite its promising prospects, the NSR presents challenges and risks due to the harsh environmental conditions, such as sea ice, low temperatures, limited infrastructure along the route, etc.

Numerous studies have investigated the feasibility of the NSR, particularly in comparison to the traditional Suez Canal Route, and have examined various factors such as political, economic, and commercial considerations (Lasserre et al., 2014; Liu et al., 2010; Xu, Yin, Jia, et al., 2011; Halvor & Svein, 2011; Cariou & Faury, 2015; Zhang, Meng, & Ng, 2016; Faury & Cariou, 2016; Hua, Dong, & Jinxian, 2018; Zeng et al., 2019). These studies have shed light on the challenges and potential countermeasures associated with the NSR, highlighting factors such as high icebreaker fees, speed and water depth limitations, and the dependence of profitability on transit speed and load factor (Verny & Grigentin, 2009; Lasserre et al., 2014).

However, while much attention has been given to the technical and operational aspects of the NSR, research on the NSR port infrastructure has been relatively limited (Ostreng et al., 2013; Daria Gritsenko & Elena Efimova, 2017; Faury et al., 2018; Wang et al., 2019; Liu et al., 2021; Hermann et al., 2022). These studies have examined various aspects of NSR ports, including cargo volume, infrastructure quality, operational status, foreign vessel access, and cargo turnover. They have highlighted the challenges faced by the Russian Arctic port system, such as long periods of ice cover, limited technical standards, insufficient water depth, and the need for infrastructure improvements. Additionally, some of these studies have analyzed the policy environment and implications for Arctic port development, considering geopolitical factors, funding possibilities, and the broader Arctic port system (Daria Gritsenko & Elena Efimova, 2017; Hermann et al., 2022).

As seen, the existing body of research on the Russian Arctic ports has primarily focused on aspects such as their development, challenges, and potential for growth. While these studies provide valuable insights into the overall landscape of the ports, important factors related to efficiency and productivity were overlooked.

Meanwhile, measuring port efficiency is crucial for promoting trade growth. As it was highlighted in the UNCTAD's Port Management Series, efficient port operations are essential for facilitating international trade, as ports serve as the primary entry and exit points for goods, directly impacting a country's ability to participate effectively in international trade. This importance is particularly emphasized for developing countries, as efficient ports are crucial for their successful integration into the global economy. In the context of the Russian Arctic, the significance of measuring port efficiency becomes even more pronounced.

Hence, our study aims to bridge this research gap by investigating the efficiency and productivity of the ports along the NSR. Such an evaluation becomes increasingly relevant nowadays, as the increasing demand for shipping along the NSR requires ports to have the necessary infrastructure and resources to handle the higher volume of traffic effectively. This may involve strategic decisions like constructing new terminals or expanding existing facilities. However, before implementing such plans, it is crucial for them to assess how effectively they have utilized their existing resources.

Thus, in this study, an attempt has been made to contribute to the literature by evaluating the efficiency of 17 ports along the NSR. To do so, we apply two models of Data Envelopment Analysis (namely CCR, and BCC) to determine their overall technical efficiency, pure technical efficiency, and scale efficiency. By analyzing efficiency of these ports individually, we aim to gain insights into their operations and identify areas for improvement.

The paper is structured as follows. After this introductory section, the literature review refers to studies on the Russian Arctic ports and those on the seaport efficiency evaluation using DEA. Next chapter presents DEA methodology and data for analysis. Chapter 4 and 5 present and discuss the results of the analysis and its policy implications. Finally, the conclusion presents the key findings, limitations, and suggestions for future studies.

Ⅱ. Literature Review

1. Research on the Russian Arctic ports

As it was stated before, the state of the NSR ports is rarely analyzed in the existing literature and the research dedicated to this topic is mostly descriptive, whereas empirical analyses are presented to a very limited extent. Here, we take a look at the handful of papers that focus on the current conditions of Russian Arctic ports.

Ostreng et al. (2013) presented a comprehensive analysis of NSR ports, covering various criteria such as operational status, foreign vessel access, services, infrastructure quality, control inspections, and cargo turnover. The study highlighted the challenges faced by the Russian Arctic port system, including long periods of ice cover, poor technical standards, insufficient water depth, and limited port facilities and infrastructure. The development of ports along the western NSR primarily resulted from increased petroleum exports, with only a few out of approximately 50 NSR ports meeting international shipping industry standards. The remaining ports predominantly served local communities, but their capacity and equipment had deteriorated, necessitating improvements.

Daria Gritsenko & Elena Efimova (2017) presents a model based on a structuration approach to analyze the policy environment for Arctic port development, using the case of Sabetta in the Yamal peninsula as an example. The study demonstrates how structural factors in the physical, economic, institutional, and environmental dimensions shape port development. It emphasizes the dynamic and multi-actor nature of port development, highlighting the importance of considering uncertainty factors and adjusting to changing operational conditions. The analysis of the Sabetta case highlights the interrelations between uncertainty factors, such as the need for inland infrastructure connections and the role of state involvement and political support. The article stresses the significance of institutional stability and the impact of climate change on port operations. The proposed analytical model serves as a decision-making tool for evaluating opportunities and constraints in Arctic port development, benefiting port authorities, project partners, and shipping/logistics companies interested in the Arctic region.

Faury et al. (2018) provided insights into the Russian Arctic port system, emphasizing the focus on exporting raw materials, particularly in the western Arctic Basin. They noted that the eastern part of the NSR has poorer infrastructure due to harsh climate conditions and a lower population density. Using Automatic Identification System (AIS) data, the study identified the Varandei port as the port with the highest cargo volume and forecasted Sabetta to become crucial due to the production of Yamal liquefied natural gas (LNG). Murmansk was recognized as the main transshipment port and an Arctic gateway, playing a pivotal role in facilitating trade in the region.

Wang et al. (2019) conducted an evaluation of 25 Russian ports, including those along the NSR, to assess their present state and future potential. Their analysis considered factors such as cargo flow, port calls, transit traffic, infrastructure, and development strategies. The study unveiled an imbalance in cargo traffic and port development along the NSR, with significant importance placed on oil and gas resources. Murmansk emerged as the largest seaport along the NSR, while ports in the Far East obtained lower potential scores but higher situation scores. Western ports exhibited better infrastructure and connection conditions compared to their counterparts along the east coast of the NSR.

Examining the impact of Russia's Arctic strategy on NSR ports, Liu et al. (2021) employed the Difference-in-Differences (DID) method to analyze the period from 2003 to 2012. Their findings highlighted the hindrances to positive port development along the NSR, primarily stemming from insufficient investment in transportation infrastructure and lagging transportation. The study also revealed that cargo throughput growth during the analyzed period was primarily driven by energy exploration, rather than the economy and foreign trade.

Hermann et al. (2022) conducted a systematic literature review on transshipment hubs in the Arctic, particularly along the Northern Sea Route (NSR). They identified four key areas of policy development: operational and design features of NSR transshipment terminals, geopolitical and governance requirements, funding possibilities, and implications for a broader Arctic port system. The study also highlighted the potential implications of the Russian-Ukrainian conflict and sanctions on transshipment hub plans in the short and medium term.

2. Research on the seaport efficiency evaluation using DEA

Along with stochastic frontier analysis (SFA), DEA is widely used for the measurement of port efficiency. First of all, this could be primarily due its ability to include multiple inputs and outputs, which is quite suitable for ports, as they produce different outputs. Another advantage of this method is that it is capable of including variables such as environment or production process attribution (Charnes et al. 1985; Seiford and Thrall 1990). These and many other DEA features have made it quite popular among scholars aiming to measure the efficiency of seaports.

The very first study that used the DEA method in the seaport context was conducted by Roll and Hayuth (1993). However, it didn't use real-world data and simply explored the possibility of applying the technique to port efficiency measurement.

Among early studies that used DEA to measure seaport efficiency, the most referred ones are Martinez-Budria et al. (1999), Tongzon (2001), Valentine and Gray (2001, 2002), Barros and Athanassiou (2004) and Cullinane et al. (2004, 2005, 2006).

Martinez-Budria et al. (1999) applied the DEA-BCC model to measure the relative efficiency of the Spanish ports during the period from 1993 to 1997. The data used included three inputs (labor expenditures, depreciation charges, and so-called "other expenditures", which are composed of intermediate inputs and services) and two outputs (the total cargo moved through the docks, measured in physical units (thousands of tons), and the revenue obtained from the rent of port facilities, measured in millions). What's significant about this study is that it is one of the first DEA studies on seaport efficiency that used time series data, which allowed authors to observe the performance of ports in dynamics, rather than in a single moment. Furthermore, the study divided ports into three categories according to their complexity (low, medium, high) in terms of their size and output composition, which made it possible to investigate whether and how the level of port complexity can affect efficiency rating. Overall, the results of the study demonstrated that ports of high complexity showed higher comparative efficiency levels, having gone closer to the frontier over time, whereas the complexity group experienced smaller growth of the efficiency levels during the five years. Finally, low-complexity ports showed a negative evolution in global efficiency levels.

Tongzon (2001) applied data envelopment analysis (DEA) to measure the efficiency of four Australian and twelve other international container ports, using the CCR and Additive Model. The study used cargo throughput as the output variable and six input variables (number of cranes, number of container berths, number of tugs, terminal area, delay time, and labor) for a single year (1996). Due to data unavailability, the author had to work with a small sample size (16 observations), which led to more ports being identified as efficient. As a result, the author suggested that it would be better to use larger samples to avoid potential biases.

Valentine and Gray (2001) investigated how the way seaports are owned and organized can determine their performance by applying the DEA-CCR model to 21 container ports from the Cargo Systems Journal 1999 list of top 100 container ports for the year 1998. Using the three different types of organization structure (simple, divisional and bureaucratic) and the four different methods of ownership (public, private, public/private, mixed), authors designed conceptual model consisting of 10 categories. Results of the study demonstrated that joint private/private ownership structure is the most efficient, while publicly owned ports are the opposite. The next year authors conducted a similar study now focusing on 19 ports in North America and Europe and the results showed similar average efficiencies for both regions. Important finding was that ownership structure didn't significantly determine the port efficiency.

Barros and Athanassiou (2004) applied DEA to estimate the relative efficiency of a sample of Portuguese and Greek seaports, using panel data between 1998 and 2000. Output variables included the ships and cargo handled, while input variables were presented by labor and capital. The results showed that most of the studied ports operated at a high level of pure technical efficiency. Also, it was found that technically efficient constant returns to scale ports also demonstrated technically efficient variable returns to scale which was the sign of scale being the dominant source of efficiency. When it comes to inefficient ports, the authors concluded that this could be due to the shortage of the dataset was short (6 DMUs).

Cullinane et al. (2004) used an extended DEA technique named DEA window analysis capable of capturing the fluctuations of efficiency over time. The study used panel data between 1992 and 1999. Container throughput was chosen as output variable and land and labour as inputs. The sample consisted of 25 ports from all over the world. This study was fundamentally different from the previous ones in terms of the type of data used. Unlike the previous studies that used cross-sectional data, which could only provide snapshots of producers and their efficiency, this one used panel data. The results indicated that the efficiency of the different container ports could change over time to different extents. Additionally, by utilizing the CCR and the BCC models, it was found that most ports exhibit constant returns to scale, which meant that production scale was not the source of inefficiency. Another important observation from the results of the study was that highly efficient ports were presented by those that did not invest actively in superstructure and/or infrastructure over time, whilst the least efficient ones were those that did that in order to increase their competitiveness in the long run.

Cullinane et al. (2005) investigated the relationship between privatization and container port efficiency by using the model and the period similar to the study conducted by Cullinane et al. (2004). The study didn't show a clear positive relation between mentioned factors and efficiency increases that happened over time was, according to the authors, more likely attributed to technological development rather than privatization.

Wang and Cullinane (2006) studied the efficiency of container terminals within the context of global supply chain management. The sample included 104 European container terminals with annual throughput of over 10 000 TEUs from 29 countries. The data gathered was for 2003 and the inputs and outputs used were quite similar to the work of Cullinane et al. (2004), except that the equipment factor was now represented by equipment costs (Wang and Cullinane, 2006).

Later, the literature has seen more studies focusing on seaport efficiency measurement within the context of different countries and regions. Pang (2006) evaluated the efficiency of 50 major ports in China by using DEA based on 3 years of consecutive data. Park (2008), Barros and Managi (2008), and Barros, Assaf, and Ibiwoye (2010) applied bootstrapped DEA to evaluate the technical efficiency of Korean container terminals, Japanese, African ports, and Brazilian ports. Rajasekar et al. (2014) examined the operational efficiency of major ports in India over the period of time 1993 to 2011 through Data Envelopment Analysis (DEA). Al-Eraqi et al. (2008) studied the efficiency of 22 seaports in the Middle East and East African region. Schøyen and Odeck (2013) evaluated the efficiency of Norwegian container ports relative to ports in the United Kingdom and Nordic countries. Nguyen (2015) applied the bootstrapped DEA method to the dataset of the 43 largest seaports in Vietnam and compared the results with those produced by the SFA and standard DEA methods.

When it comes to Russian ports, literature is very scarce. Kharchenko (2013) assessed the effectiveness of Vladivostok and Nakhodka, seaports in the Far East of Russia, using SFA, DEA, and PPM. Kuznetsov et. al (2007) showed the possibility of applying DEA for evaluating container terminals' efficiency, using Korean container terminals' data for 1999-2002 (Busan, Sebang, Hanjin, Hutchison, and Korex) as an example. Mariia Den et al. (2016) measured and compared the relative efficiency of Russian and Korean container terminals utilizing DEA.

As can be seen from this literature review, while DEA has been widely used to evaluate seaport efficiency in various regions and countries, its application to Russian ports is still limited. Moreover, previous research has not encompassed those along the Russian Arctic coastline. Hence, applying DEA methodology to assess the efficiency of these ports is a novel contribution.

Furthermore, as it was mentioned before, previous studies on these ports have predominantly focused on aspects related to their development, challenges, and potential while overlooking their key performance indicators such as efficiency and productivity. Therefore, our study not only extends the application of DEA methodology to the previously unexplored context but also contributes to the existing literature on Russian Arctic ports.

Ⅲ. Research Design

1. Data Envelopment Analysis Overiew

The data envelopment analysis (DEA) method is a data-oriented approach for evaluating the performance of a set of peer entities called Decision-Making Units (DMUs), which convert multiple inputs into multiple outputs (Cooper et.al, 2010). Decision-Making Units (DMUs) can be represented by various kinds of entities (governments, business firms, not-for-profit organizations, schools, hospitals, etc.). The ideas of this method were originally introduced by Farrell (1957) and then were advanced by Charnes et al. (1978), who used DEA to evaluate the activities of not-for-profit entities participating in public programs. The methodology introduced by these authors is known as the DEA-CCR model (due to Charnes, Cooper, and Rhodes). Later, Banker et al. (1984) introduced the DEA-BCC model (due to Banker, Charnes, and Cooper). Since the introduction of these models, there have been several extensions to the DEA in terms of its theory, methodology, and application.

Our study utilizes the two most widely used DEA models, DEA-CCR and DEA-BCC and DEA-based Malmquist productivity index.

The CCR model is utilized to estimate the overall technical efficiency (TE) assuming that returns to scale are constant.

Mathematically, the CCR model is expressed as:

$$\max h_0 = \frac{\sum_{r=1}^{s} u_r y_{r_0}}{\sum_{i=1}^{m} v_i x_{ij}}$$

$$s.t. \ = \ \frac{\sum_{r=1}^{s} u_r y_{r_0}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1, \ j = 1,2 \cdots, \ n$$

$$u_r \ge \epsilon \rangle 0, \ r = 1,2 \cdots, s.$$

$$v_r \ge \epsilon \rangle 0, i = 1,2 \cdots m.$$

ho: Efficiency of DMU

s.t.: Weight for output

vi: Weight for input i

ur: r-th output amount of DMU

xi: j-th input amount of DMU

ui: r-th input amount of DMU

m: Non-Archimedes constant

n: Number of DMU

m: Number of inputs

s: Number of outputs

The BCC model with the assumption of variable returns to scale is applied to estimate the pure TE of a decision-making unit (DMU) at a given scale operation.

The BCC model is expressed as:

$$\max h_0 = \frac{\sum_{r=1}^{s} u_r y_{r_0} + U_0}{\sum_{i=1}^{m} v_i x_{i0}}$$

$$s.t. \;=\; \frac{\sum_{r=1}^{s} u_r y_{r_j} + U_0}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1,\; j = 1,2 \cdots,\; n$$

$$u_r \geq \epsilon \rangle 0,\; r = 1,2 \cdots, s.$$

$$v_r \geq \epsilon \rangle 0, i = 1,2 \cdots, m.$$

ho: Efficiency of DMU

s.t.: Weight for output

vi: Weight for input i

ur: r-th output amount of DMU

xi: j-th input amount of DMU

ui: r-th input amount of DMU

m: Non-Archimedes constant

n: Number of DMU

m: Number of inputs

s: Number of outputs

When deciding on models to run, one can choose between input-oriented and output-oriented ones. The first focuses on the movement toward an efficiency frontier by the proportional reduction of production inputs and the second focuses on the movement toward the frontier by the proportional expansion of production outputs. Additionally, output-oriented models are more associated with planning and strategy formulation, while input-oriented models are closely related to operational and managerial issues (Wang et al.,2003). For our study, we decided to choose the output-oriented model since it seems to suit the best when selected inputs are physical (related to infrastructure) (Yuen et al., 2013).

Having applied both models we then calculate the overall efficiency (technical and scale), using the formula SE = TE/PTE. This ratio represents the object's efficiency in relation to the optimal scale that allows for the maximum utilization of inputs.

2. Preparing dataset

When selecting DMUs and variables, one should take into account two important considerations, which are their number and type. There are some studies that have proposed guidelines on the number of inputs, outputs, and DMUs to ensure good discriminatory power in DEA models.

Boussofiane et al. (1991) suggest that the number of DMUs should be at least the multiple of the number of inputs and outputs. Golany and Roll (1989) recommend having at least twice the number of DMUs as there are inputs and outputs. Bowlin (1998) suggests three times the number of DMUs as there are input and output variables, while Dyson et al. (2001) propose two times the product of the number of input and output variables. These guidelines provide minimum thresholds for ensuring reasonable discriminatory power in basic productivity models.

In our study, 17 DMUs and four variables (3 inputs, 1 output) were chosen based on data availability and adhering to the recommendations made by the mentioned researchers (Table 1).

When it comes to the entity type of our DMUs, we chose port authorities as our DMUs. Ideally, rankings of relative efficiency are most meaningful when comparing ports that compete with each other. However, in the case of the

Russian Arctic port system, the concept of port competition may not apply as strongly there due to the unique regional characteristics and the limited number of ports. Considering that our study only focuses on understanding the efficiency and performance of the NSR ports, not comparing them based on competition, the choice of port authorities as DMUs is acceptable and can still provide meaningful insights into their performance.

〈Table 1〉 List of DMUs

DMUs	Seaport	Area
DMU1	Murmansk	Western Arctic
DMU2	Kandalaksha	Western Arctic
DMU3	Onega	Western Arctic
DMU4	Arkhangelsk	Western Arctic
DMU5	Mezen'	Western Arctic
DMU6	Naryan-Mar	Western Arctic
DMU7	Varandei	Western Arctic
DMU8	Sabetta	Western Arctic
DMU9	Dikson	Western Arctic
DMU10	Dudinka	Western Arctic
DMU11	Khatanga	Eastern Arctic
DMU12	Tiksi	Eastern Arctic
DMU13	Anadyr	Eastern Arctic
DMU14	Pevek	Eastern Arctic
DMU15	Provideniya	Eastern Arctic
DMU16	Evgekinot	Eastern Arctic
DMU17	Beringovskiy	Eastern Arctic

Furthermore, the choice of NSR port authorities as our DMUs seems to be reasonable given the highly centralized port system in Russia. For reference, port governance in Russia is performed by two bodies: Rosmorport and the Seaport Administration (Daria Gritsenko & Elena Efimova, 2017). The roles and responsibilities of these bodies are well-defined, with Rosmorport focusing on the organization, maintenance, and development of port infrastructure, while the Seaport Administration manages the federal property and ensures the functioning of the port as a commercial entity. These two bodies provide port authorities with significant influence and control over the port operation and development, which makes them a suitable entity to consider when assessing the efficiency of the NSR ports.

The efficiency of a container terminal and/or port often depends on the efficient use of labor, land, and equipment, and therefore, in order to estimate it, one should choose variables that fall into these categories. We were able to obtain infrastructure-related inputs that are normally represented by variables, such as the total quay length, terminal area, the number of gantry cranes, yard gantry cranes, and straddle carriers.

As our output variable, we selected cargo throughput, the most commonly used output variable in the literature. A critical review of the literature on measuring seaport efficiency by using DEA undertaken by Panayides et al (2009) revealed almost all of the research covered had chosen cargo throughput as the dominating output variable in assessing port/terminal production efficiency, due to the relative ease in data collection. Cullilane and Wang (2007) highlighted that cargo throughput is the most appropriate and analytically tractable indicator of the effectiveness of the production of a port.

In our study, based on data availability and the summary of inputs and outputs used in previous relevant studies (Table 2), three inputs (the number of berths, quay length, handling capacity) and one output (cargo throughput) were chosen (Table 3).

〈Table 2〉 Overview of studies applying DEA to the seaport industry

Author(s)	DMUs	Period	Model	Input(s)	Output(s)
Martinez-Budria et al. (1999)	26 Spanish ports	1993-1997	BCC	(3) labor expenditure; depreciation charges; and "other expenditures"	(2) the total cargo moved through the docks and the revenue obtained from the rent of port facilities
Tongzon (2001)	16 Australian (4) and international container ports (12)	1996	CCR and Additive Model	(6) number of cranes, number of container berths, number of tugs, terminal area, delay time, and labor	(2) cargo throughput, ship working rate

Valentine and Gray (2001)	31 container ports	1998	CCR	(2) container and overall quay length	(2) container throughput and total throughput
Barros and Athanassiou (2004)	6 Portuguese and Greek seaports	1998-2000	CCR BCC	(2) number of workers and the book value of assets	(4) ships, movement of freight, total cargo handled, containers loaded and unloaded
Cullinane et al. (2004)	25 ports from all over the world	1992-1999	CCR BCC And DEA-Window Analysis	(5) quay length, terminal area, number of quay and yard gantry cranes, the number of straddle carriers	(1) container throughput
Cullinane et al. (2005)	57 entities, either container ports or individual terminals within container ports from over the world	1999	CCR BCC FDH (Free Disposal Hull)	(5) quay length, terminal area, number of the quay and yard gantry cranes, the number of straddle carriers	(1) container throughput
Cullinane et al. (2006)	25 world's leading container ports 5 Chinese container ports	1992-1999	CCR, BCC, CCR intertemporal analysis, BCC intertemporal analysis	(5) quay length, terminal area, number of quay and yard gantry quay cranes, the number of straddle carriers	(1) container throughput
Cullinane et al. (2007)	104 European container terminals	20202	CCR BCC	(3) terminal length terminal area, equipment	(1) container throughput

Mariia Den et al. (2016)	31 container terminals in Russia (12) and Korea (19)	2012-2014.	Output-oriented Window DEA	(7) total terminal area; total quay length; quay equipment; yard equipment; storage capacity; depth alongside; handling capacity	(1) annual container throughput
Ye et al. (2020)	22 major ports along the Yangtze River	2010-2016	slacks-based measure (super-SBM) model and the MPI	(3) quay line length, berth number, channel dredging depth	(2) cargo throughput, container throughput
Huang et al. (2021)	11 crucial ports along the twenty-first Century Maritime Silk Road	2013–2017	The DEA–supply chain operations reference (SCOR)	(3) container berth wharf length number of gantry cranes	(1) container throughput
Kuo et al. (2020)	53 ports in Vietnam	2012-2016	Context-dependent DEA-model	(3) total terminal area terminal length equipment	(1) throughput ship calls
Al-Eraqi et al. (2008)	22 seaports in the Middle East and East African region	2000–2005	DEA-CCR DEA-BCC DEA-Window Analysis	(3) berth length, storage area, handling equipment	(2) ship calls, throughput

〈Table 3〉 Variables description

Variables	Definitions	Units
Berths (I1)	Number of berths	Unit
Quay length (I2)	Length of the seaport quay front	m
Terminal throughput capacity (I3)	The capacity of cargo terminals in total	ton
Cargo throughput (O1)	The weighted quantity of cargo handled annually	ton

〈Table 4〉 Correlation matrix of inputs and output in 2018

	Number of Berths	Quay length	Terminal throughput capacity	Cargo throughput
Number of Berths	1	0,996	0,630	0,806
Quay Length	0,996	1	0,677	0,820
Terminal throughput capacity	0,630	0,677	1	0,784
Cargo throughput	0,806	0,820	0,784	1

After selecting variables for our study, we conducted a correlation analysis to examine the relationships between these variables (Table 4). If we take a look at the correlation matrix of inputs and outputs, there are strong positive relationships between the variables. For example, there is a very high positive correlation between the number of berths and quay length, indicating that as the number of berths increases, the quay length tends to increase as well. Normally, in such a case, one would consider addressing the high correlation by either removing one of the correlated variables or combining them into a composite variable that better captures the underlying construct. However, in our case, data availability remains a significant challenge, so we had no other option rather than to retain highly correlated variables.

The data for input variables were taken from the Russian Federation Register of Seaports, which is run by the Russian Federal Agency for Marine and River Transport, and the official website of the Center of the Ministry of Transport of Russia. The cargo throughput data were mostly obtained from the Russian Association of Sea Commercial Ports' s analytical journal "Morskiye Porty".

Ⅳ. Results

The estimates for all three years are given in Table 5. TE represents the CCR model technical efficiency, PTE indicates the BCC model pure technology efficiency, and SE stands for scale efficiency. The ports that obtained a score equal to 1.00 are considered efficient, whereas those with less than 1.00 are treated as inefficient.

In 2018, seven out of the 17 NSR ports evaluated (DMU1, DMU2, DMU7, DMU8, DMU12, DMU16, DMU17) were found to be efficient according to the DEA-BCC model. The DEA-CCR model, on the other hand, identified only two efficient ports (DMU1, DMU7). In 2019, the DEA-BCC model identified six efficient ports (DMU1, DMU2, DMU7, DMU8, DMU12, DMU17), while the DEA-CCR model identified four efficient ports (DMU1, DMU7, DMU8, DMU17). Moving to 2020, the DEA-BCC model identified five efficient ports (DMU1, DMU7, DMU8, DMU12, DMU17), and the DEA-CCR model also identified four efficient ports (DMU1, DMU7, DMU8, DMU17).

The DEA-BCC model consistently identified more efficient ports compared to the DEA-CCR model across all three years. In 2018, the average efficiency value for the BCC model was 0.63, while the CCR model had an average efficiency value of 0.36. Similarly, in 2019, the BCC model had an average efficiency value of 0.60, compared to the CCR model's average efficiency value of 0.39. In 2020, the BCC model yielded an average efficiency value of 0.58, while the CCR model had an average efficiency value of 0.36.

As one can notice, for all the inefficient DMUs, the CCR efficiency is lower than the BCC efficiency, which suggests a consistent trend of scale inefficiency. This indicates that these DMUs are operating at a suboptimal scale, and there might be room for improvement by either increasing or decreasing their operations to achieve a better balance between inputs and outputs.

Training the BCC model also provides detailed information about slacks, which are the unused or underutilized resources (inputs) or excess outputs of a decision-making unit (DMU) relative to the efficient frontier. Our BCC model identified excess in two inputs (number of berths and quay length) for several DMUs. In 2018, slacks in the utilization of the number of berths were found for six DMUs: DMU3, DMU4, DMU6, DMU11, DMU13, and DMU17. Among them, DMU4 (Arkhangelsk) had the largest slack of 25 (out of 75), followed by DMU3 (Onega) with a slack of 4(out of 7), and DMU6 (Naryan-Mar) and DMU11 (Khatanga) with slacks of 2(out of 6) and 3(out of 5), respectively. The situation remained relatively unchanged in 2019 and 2020, except for DMU6, DMU13, and DMU17, which eliminated their slacks. Both in 2019 and 2020, DMU3, DMU4, and DMU11 consistently exhibited slacks in the number of berths they utilized, amounting to 2, 24, and 3, respectively. These findings indicate that at the time these DMUs were utilizing more berths than necessary to achieve their desired output levels.

〈Table 5〉 The Results of the DEA-CCR and DEA-BCC Models

DMU	2018				2019				2020			
	TE	PTE	SE	RTS	TE	PTE	SE	RTS	TE	PTE	SE	RTS
DMU1	1,000	1,000	1,000	CRS	1,000	1,000	1,000	CRS	1,000	1,000	1,000	CRS
DMU2	0,773	1,000	0,773	IRS	0,849	1,000	0,849	IRS	0,335	0,439	0,762	IRS
DMU3	0,144	0,187	0,771	IRS	0,133	0,133	1,000	CRS	0,090	0,091	0,989	CRS
DMU4	0,103	0,104	0,997	IRS	0,098	0,098	0,999	CRS	0,125	0,132	0,948	CRS
DMU5	0,050	1,000	0,050	CRS	0,029	0,999	0,029	CRS	0,013	0,997	0,013	CRS
DMU6	0,093	0,105	0,882	IRS	0,125	0,125	1,000	IRS	0,065	0,065	1,000	IRS
DMU7	1,000	1,000	1,000	CRS	1,000	1,000	1,000	CRS	1,000	1,000	1,000	CRS
DMU8	0,868	1,000	0,868	DRS	1,000	1,000	1,000	CRS	1,000	1,000	1,000	CRS
DMU9	0,061	1,000	0,061	CRS	0,058	1,000	0,058	CRS	0,034	0,999	0,034	CRS
DMU10	0,302	0,325	0,931	IRS	0,329	0,349	0,941	IRS	0,341	0,368	0,926	IRS
DMU11	0,107	0,293	0,366	IRS	0,152	0,289	0,528	IRS	0,073	0,133	0,546	IRS
DMU12	0,100	1,000	0,100	IRS	0,211	1,000	0,211	IRS	0,241	1,000	0,241	IRS
DMU13	0,103	0,110	0,933	IRS	0,041	0,043	0,957	IRS	0,095	0,102	0,933	IRS
DMU14	0,423	0,542	0,781	IRS	0,439	0,544	0,808	IRS	0,373	0,509	0,733	IRS
DMU15	0,023	0,033	0,706	IRS	0,021	0,025	0,836	IRS	0,021	0,026	0,812	IRS
DMU16	0,256	1,000	0,256	IRS	0,149	0,628	0,238	IRS	0,239	1,000	0,239	CRS
DMU17	0,727	1,000	0,727	IRS	1,000	1,000	1,000	CRS	1,000	1,000	1,000	CRS

Further examining the excess utilization of quay length, our analysis revealed significant slacks in this aspect for a total of six DMUs. Interestingly, among these DMUs, we observe that DMU3, DMU4, DMU6, and DMU11, which had significant slacks in the number of berths, also exhibit considerable slacks in the utilization of quay length. This suggests a potential inefficiency in the allocation and utilization of both berths and quay length for these specific DMUs.

As can be seen from the result of our analysis, the ports that were evaluated as efficient are mostly presented by the western NSR ports. Notably, DMU1 (Murmansk), and DMU7 (Varandei) are treated as efficient in all cases (all scales and years) and demonstrate constant returns to scale. This suggests that these DMUs are utilizing their inputs effectively to generate the maximum level of output possible, given the resources available to them.

Ⅴ. Results Discussion and Policy Implications

The scores obtained from training DEA-CCR and DEA-BCC demonstrate that the efficient ports predominantly belong to the western NSR region, with DMU1 (Murmansk) and DMU7 (Varandei) consistently demonstrating efficiency and constant returns to scale across all scales and years.

The high efficiency of the western Arctic ports can be attributed to several factors. Firstly, these ports benefit from favorable geographical conditions, which include natural deep-water harbors and ice-free periods, allowing them to operate year-round. Additionally, the Western ports have better transport connectivity. Furthermore, it is important to highlight their proximity to oil and gas production sources, which probably plays a significant role in their utilization. Given the heavy reliance of the Russian economy on natural resource exports, it is unsurprising that these ports operate at maximum capacity.

When it comes to inefficient ports, significant factor to consider when interpreting the results should be the impact of the short navigation season in the NSR, which varies from year to year. We assume that restricted timeframe for operations due to the short navigation season may pose challenges for the ports in fully utilizing their resources and achieving higher efficiency levels. It's also worth noting that the global COVID-19 pandemic may have had an impact on the efficiency of the ports during the studied period. The pandemic caused disruptions in international trade and shipping, leading to changes in demand patterns and operational restrictions. These factors could have also affected the ports' ability to operate efficiently and maximize resource utilization.

Additionally, our analysis provided some valuable insights into the underlying causes of inefficiency among NSR ports. Specifically, the insights derived from the BCC model's outcomes highlight that inefficiencies are predominantly rooted in ineffective allocation and utilization of resources. Notably, training the BCC model provides comprehensive insights into "slacks," which signify underutilized or surplus resources (inputs) or excess outputs of a decision-making unit (DMU) concerning the efficient frontier.

Our BCC model identified excess in two inputs (number of berths and quay length) for several DMUs. In 2018, slacks in the utilization of the number of berths were found for six DMUs: DMU3, DMU4, DMU6, DMU11, DMU13, and

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Based on these findings, the following suggestions and policy implications can be drawn. Turning our attention to ports that have shown limited use of both berths and quay lengths, specifically DMU3 (Onega), DMU4 (Arkhangelsk), DMU6 (Naryan-Mar), and DMU11 (Khatanga), it becomes crucial to address these inefficiencies in a timely manner. Policymakers should closely collaborate with these ports to accurately assess the length of quays they need. Implementing strategies to make better use of the available quay space is essential for enhancing overall efficiency.

Next, similarly important is the efficient deployment of the required number of berths to match the desired operational levels. Ensuring that these ports are making effective use of their berths is vital for reducing underutilization and maximizing their operational capacity.

Finally, given the variability in the navigation season from year to year, ports should consider implementing a monitoring system that regularly gauges port efficiency and provides timely feedback. By leveraging historical data and trends, ports would be able to better anticipate the resource requirements and operational challenges associated with different navigation seasons. This predictive element would empower ports to pre-emptively adjust their resource allocation strategies, ensuring optimal efficiency during each season.

Here, we would like to acknowledge that our discussion on the causes of inefficiencies is only based on assumptions drawn from available data and our understanding of the industry. These assumptions should be regarded as preliminary insights rather than definitive conclusions. A more comprehensive analysis, incorporating in-depth qualitative research, interviews with key stakeholders, and even potential collaboration with domain experts, is necessary to truly uncover the root causes of inefficiencies with a higher degree of accuracy.

Ⅵ. Conclusion

This study evaluated the efficiency of 17 ports along the NSR in 2018-2019, utilizing the two most widely used DEA models, DEA-CCR and DEA-BCC. Then, the DEA Malmquist productivity index was utilized to examine efficiency gains in the whole research period (2018–2020). Our study assumed three inputs (number of berths, quay length, handling capacity) and one output (cargo throughput).

Several key findings were obtained regarding the efficiency of ports in the Northern Sea Route (NSR). The efficient ports primarily belong to the western NSR region, with Murmansk and Varandei consistently demonstrating efficiency and constant returns to scale across all scales and years. Findings also highlight areas for improvement in resource allocation and utilization. Ports such as Onega, Arkhangelsk, Naryan-Mar, and Khatanga exhibited slacks in the utilization of berths and quay lengths, indicating inefficiencies in resource allocation.

In summary, the analysis suggests that while certain ports in the western NSR region operate efficiently and benefit from favorable conditions, there is still potential for improving resource allocation and utilization.

However, when interpreting the results and considering the applicability of our findings one should keep in mind that our research has a few limitations. First, data availability restricted the inclusion of important factors such as labor productivity and equipment utilization, limiting the comprehensive assessment of efficiency. Also, the exclusive reliance on cargo throughput as the output variable may not capture the full scope of port performance.

Next, the presence of strong positive correlations among input and output variables is another limitation. This indicates interdependencies between variables, such as the relationship between quay length and a number of berths. In a typical analysis, highly correlated variables would be addressed by either removing one or creating a composite variable. However, due to data availability constraints, we were unable to address this issue adequately. While this decision may not align with the ideal statistical practices, it was a practical choice based on the available data.

Despite these limitations, our research still provides insights into optimizing resource allocation, and enhancing operational practices of NSR ports and can serve as a foundation for further development of evaluation models. Future studies should consider contextual factors specific to the Arctic region and aim to incorporate a more comprehensive range of variables as data availability improves.

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A Study on Port Efficiency in the Russian Arctic as a Key Factor for Trade Growth in the Northern Sea Route

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Abstract

The rapid melting of Arctic sea ice has increased interest in the Northern Sea Route (NSR) as a viable alternative trade route between Europe and Asia. While extensive research has examined its competitiveness in terms of technical feasibility, safety, profitability, and environmental impact, the topic of the NSR ports remains relatively underrepresented in the literature. Hence, this study aims to contribute to the existing research by assessing the efficiency of 17 NSR ports to gain insights into their operations and identify areas for improvement using models of Data Envelopment Analysis(DEA). The obtained results show that efficient ports mainly belong to the western NSR region, with ports like Murmansk and Varandei consistently demonstrating high efficiency and constant returns to scale. Several ports, such as Onega, Arkhangelsk, Naryan-Mar, and Khatanga, showed inefficiencies in the utilization of berths and quay lengths. The findings not only contribute to academic knowledge but also offer practical implications for NSR port authorities, assisting them in making well-informed decisions regarding infrastructure development plans.

〈Key Words〉 Port efficiency, Northern Sea Route, Russian Arctic, DEA, Malmquist Productivity Index Trade strategies