ISSN No:-2456-2165

A Linear Programming Optimization Approach to Costs Minimization in Port Terminal Operations in Nigerian Ports

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Abstract:- The study evaluated optimization as a quantitative approach to minimizing the costs of terminal operations in comparison with the routine (trial and error) approach found to be employed by terminal operators in Nigerian ports. To carry out the experimental survey, five-year throughput data of dry and liquid bulk cargoes from a bulk terminal operator at Port Harcourt NPA Port were collected from 2015 to 2019 to serve the routine approach purpose. In parallel an objective function was modelled to minimize the costs of cargo handling subject to identified constraints that produced the optimal solutions for the optimized data. A test of hypothesis was conducted to determine if the means (μ) of the two sets of data (optimization and routine)were significantly different from each other using the student t-test statistic. At 95% level of significance, degree of freedom (df) 4, the results revealed that there was no significant difference between the two data sets. The paper concluded with the implications for the study and the need to train both the terminal operators and the ports authority in the use of the optimization techniques for an integrated to tackling port operational challenges.

***Keywords**:- Dry/Liquid Bulk, Cargo Throughput, Guaranteed Minimum Tonnage (GMT), Optimized Cost Projections, Technical Efficiency.*

I. INTRODUCTION

The intricacies of modern ports in terms of size, ownership structure and technical developments to accommodate the ever-growing ships being turned out from shipyards put tremendous pressure on ports and terminals handlers. This is particularly so with ports that were not originally designed as deep sea or mega ports but which have to upgrade facilities to match growing traffic. Higher stakes in private capital investments, increased service demands from shippers and freight forwarders; higher commitments to ports authorities, the customs and other ports agencies as well as shipping lines, make decision-making by terminal managers volatile. Meeting these responsibilities have ostensibly been the underlining basis for the various innovations that the port industry has witnessed. Since the era of port privatization which saw port capital investments take a leap albeit alongside operational overheads, awareness about keeping the costs of operation low in order to remain above board has also soared. As a terminal's output is measured in terms of the volume of import and export cargo it handles over a given period, a terminal is deemed to be operating at optimal capacity when its output approaches increasing returns to scale – that is when its throughput rises by a higher proportion compared to its inputs. In the face of relatively scarce resources, terminal operators concern themselves, justifiably so, with technical efficiency, that is those aspects of efficiency concerned with generating the largest possible cargo throughput for given inputs; or the smallest possible inputs for given outputs.

In the Nigerian port industry, the port authority known as landlord/lessor, in line with global practice, has amongst other demands, set 'productivity target' known as *guaranteed minimum tonnage* (GMT) for terminal operators (lessees) to meet annually since 2006 when the ports were privatized and the terminals concessioned to private firms. This onerous expectation of the port less or from its lessees makes the need for technical efficiency by the terminal operators all the more compelling. No doubt investment in port terminals is a huge venture, often involving huge sums in *sunk* (irrecoverable) costs. Moreover, all operators face time constraint in the form of terminal lease (concession years) which puts a ceiling on the time they have available to the investors to operate their terminals, deliver the annual guaranteed minimum tonnage as well as pay statutory royalties and due; carry out necessary terminal upgrades, and make good returns on their investments. With the maximum terminal concession in Nigeria's ports being twenty-five years, there is the acute awareness amongst the lessees that they do not have that much latitude to keep on managing operations simply on routine basis, even as constantly changing technology keeps the operators on their toes to meet up with the competition.

As ships arrive and depart a port, they exact the highest level of responsibility on the port authority and its terminal operators for pilotage, towage, mooring, cargo loading and unloading and storage services; the ultimate goal being reduction in ship turn-around time (STAT) and cargo dwell time (CDT) (Rodrigue, 2020).These high expectations provide justifiable basis for not leaving operational decisions to routine guesswork because of the grave implications (Shah, Gor, & Soni, 2010).By extension, quite a number of “innovative processes”(Acciaro, et al., 2018) have been adopted in contemporary ports management forbetter handling of port investments towards improving ports and terminals productivity. Some of these innovationsare the Multi-Agent System (MAS) Architecture (Rebollo, et al., 2001); Asset Management (Theofanis, et al., 2007); andInvestment Assessment (Zheng & Negenborn, 2017), amongst others.These processes adopt optimization techniques in one form or another.

This study was carried out to assess the efectiveness of optimization on terminal costs of operation in minimization in a bulk terminal that handles liquid and dry cargo at Terminal A of Port Harcourt NPA Port, Rivers State, Nigeria.The researchersapplied thelinear programming (LP) optimization technique(graphical approach) to generate *optimized data* parallel to the five-year throughput operational data supplied bythe respondents on routine (trial and error) basis.The rest of the paper describes theprocesses of making comparative evaluation betweenthe operator’s routine approach and the researchers’ optimization approach to minimizing the terminal operational costs.

Problem Statement

The eastern ports of Nigeria, under which the terminal of study is situated, has been notorious for theproblem of perennial low ship traffic over time (Okeudo, 2013; Salau, 2017; Salau, 2018; Bivbere, 2018). This suggests capacity underutilization from the factors of productionemployed by the operators of the ports. The low utilization ofcapacity from the employment of land (berths and storage sheds), labour (dock workers), capital (fixed and mobile cargo handling plants) and entrepreneurship (innovative ideas for managing operations)is symptomatic of loss of income and ultimately of terminal investments. Whilst the terminal operators in the ports are desirous of curtailing wastage of their assets in view of the poor ship calls to the ports, the reconnaissance survey revealed that the operators had no methodical approach to allocating resources. Rather, they take operational decisions on routine trial-and-error basis which has done very little or nothing to improve the condition of excess capacity. No doubt the trial-and-error approach is based on intuition and is often prone to error (Nguyen, Etsuko, & Akio, 2009).As the bulk cargo terminal operator in this study has not fared any better than the other operators in the eastern ports in terms of their approach to resources management, the researchers saw a need to introduce a quantitative approach to managing the operations so as to cut the losses from unsued capacity. The reasoning behind this approach is that resources that are not deployed in operations can find better use in rent and earn income for their owners (the operators). This is particularly so with mobile cargo handling equipment.

II. RELATED LITERATURE

Srivastava, Shenoy, & Sharma, (2009) capture the essence of adopting quantitative approaches to managing complex and/or critical operations. In their words: *Managerial activities become more complex as the organizational settings in which they have to be performed become complex. As the complexity increases, management becomes more of a science than an art and a manager by birth yields place to a manager by profession.* By this token, port literature on optimization’s application to terminal operations generally agree that integrated planning of port operations significantly enhances terminal efficiency by more effective utilization of the limited resources of the port and allows a terminal have improved control on its performance. Diverse application of optimization includes to container terminals in the ports of Antwerp (Belgium) and Gioia Tauro (Italy) to resolve berth and block allocation problem (Vacca, Bierlaire, & Salani, 2007); to resolve the problem of waste of storage tank space in an oil terminal in the Port of Santos (Brazil) in allocation of bulk liquid cargo to different clients due to the manual computations used by the terminal operators (Caixeta-Filho, Piccoli, & Piccoli-Filho, 2001); to resolve Berth Allocation Problem (BAP) for dry bulk vessels in United Arab Emirates (UAE’s) SAQR Port, Ras Al Khaimah (Umang, Bierlaire, & Vacca, 2011); and to find the best possible assignment of products to dedicated storage tanks in a Tank Farm Operation Problem (TFOP) (Terrazas-Moreno, Grossman, & Wassick, 2012). In some unique applications, optimization was combined with discreet event simulation as part of a comprehensive decision support system for more accurate results in cost and time savings in product allocation to storage tanks(Sharda & Vazquez, 2009).A common thread in the foregoing works is that the ports and terminals in which optimization was applied functioned at their full capacity, with regular ship traffic which appears to be taken for granted. This is at variance with present study wherein the port in which the optimization approach is being attempted suffers from low ship traffic which is a major factor affecting the designing of the models. This is a significant gap in the literature that this work is set to fill.

In conclusion, optimization’s growing popularity as a tool of analyses of port operations notwithstanding, its weakness is believed tolie in its angling for diverse mathematical processes amid the tons of data which a researcher has to literally wade through to establish trends, develop models and analyze possibilities to obtain prescient results for decision-making (Wright, 2016). Given the difficulty of keeping detailed and accurate data in developing countries, not excepting Nigeria, it is perhaps why port operators have not been disposed to embracing not just optimization but other quantitative tools for making decisions, albeit the awareness of such approaches and their importance to overall port productivity is not lacking to stakeholders (Haralambides, 2017). As shown in the literature, adopting quantitative approaches like optimization drawn from operations research and other numerate disciplines have become a *fait accompli* in ports

ISSN No:-2456-2165

operations management. It is a trend that is set to keep growing rather than abate.

III. MATERIALS AND METHODS

The study employed a survey approach with secondary data source. The Researchers compiled five-year cargo throughput records (in metric tons) of a dry and liquid bulk cargo terminal operator at the Port Harcourt NPA Port in Rivers State Nigeria, spanning 2015 to 2019. The throughput data were based on the annual guaranteed minimum tonnage (GMT) projected for the operator by the Nigerian Ports Authority (NPA). The data are presented in Table 1 below:

Table 1:Bulk terminal operator's projected throughput for dry bulk and liquid bulk cargoes

Period	Dry bulk cargo (tons)	Liquid bulk cargo (tons)	Total
2015	4,013,645	3,283,927	7,297,572
2016	3,065,405	5,692,894	8,758,299
2017	5,254,972	5,254,972	10,509,944
2018	7,567,159	5,044,773	12,611,932
2019	9,080,590	6,053,726	15,134,316

Source: Field study, January, 2020

From the operator's *modus operandi* three resources were identified as key to meeting the projected throughput in Table 1. These are storage space (warehouse for dry bulk and storage tanks for liquid cargo); dock labour (paid hourly wages per man hour); and the storage period (in hours) for cargo. To formulate the cost minimization objective, the minimum amount of each of the resources required per operational shift alongside the minimum amount consumed per cargo type(notated x_1 and $x_2$for dry bulk and liquid bulk respectively)plus the cost per ton of cargo were extrapolated from the operator's records, as follows:

Table 2: Terminal input resources required per operational shift of dry bulk and liquid bulk cargo handling

Resource	Dry bulk cargo (x_1)	Liquid bulk cargo (x_2)	Minimum usage level per shift
Storage space (warehouse & storage tanks)	100 cu. meters	20 cu. meters	600 cu. meters
Dock labour	5 men	2 men	40 men
Storage time (hours)	15 hrs	30 hrs	180 hrs
Handling cost per ton of	$10	$4	

Source: This study, January 2020

Applying the LP optimization approach to the input resources in Table 2, the cost minimization objective model was formulated and takes the form:

$$Minimize\ Z = 10x_1 + 4x_2 \ldots\ldots\ldots\ldots objective\ function$$

Subject to satisfying the following constraints:

Storage space constraint: $100x_1 + 20x_2 \geq 600$

Dock labour personnel constraint: $5x_1 + 2x_2 \geq 40$

Storage time constraint: $15x_1 + 30x_2 \geq 180$

$x_1,\ x_2 \geq 0$ non-negativity constraints

The feasible region is identified by solving the constraint inequalities, thus given:

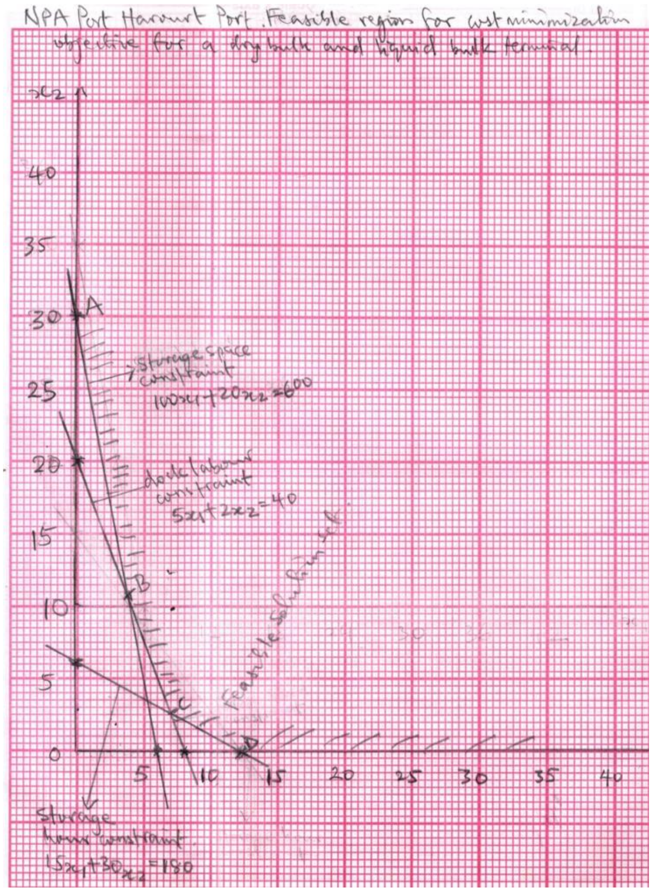
Storage space constraint:$100x_1 + 20x_2 = 600 \rightarrow x_1 = \frac{600}{100} = 6;\ x_2 = \frac{600}{20} = 30$

Dock labour personnel constraint: $5x_1 + 2x_2 = 40 \rightarrow x_1 = \frac{40}{5} = 8;\ x_2 = \frac{40}{2} = 20$

Storage hour constraint: $15x_1 + 30x_2 = 180 \rightarrow x_1 = \frac{180}{15} = 12;\ x_2 = \frac{180}{30} = 6$

The feasible region that fits the optimal solution for the minimization objective function is graphed and presented in figure 1 as follows:

Figure 1: Feasible region for the cost minimization objective of the bulk terminal operator at NPA Port Harcourt Port



Source: This study, January 2020

The vertices of the feasible region ABCD in the graph (figure 1) which define the parameters that would minimize the cost of operation for the terminal operator based on the input constraints are identified as below:

Table 3: Feasible region based on figure 1

	X_1	X_2
A	(0,	0)
B	(3.5,	11)
C	(7,	2.5)
D	(12,	0)

Thus the vertices in the feasible solution sets at points ABCD for the minimization objective is given as: **Minimize $Z = 10x_1 + 4x_2$**

Hence at points
A = 10 (0) + 4 (0) = \$0
B = 10 (3.5) + 4 (11) = 35 + 44 = \$79
C = 10 (7) + 4 (2.5) = 70 + 10 = \$80
D = 10 (12) + 4 (0) = 120 + 0 = \$120

From the feasible region, the optimal solution for the cost minimization objective is met at point B, at the cost of \$79 where the terminal delivers 3.5 tons of dry bulk cargo (x_1) and 11 tons of liquid bulk cargo (x_2). Given the five-year projected throughput presented in Table 1, the corresponding costs of cargo handling recorded by the terminal over the period was noted (based on terminal records) and compared with the cost of cargo handling based on optimization/cost minimization objective. As expected, the total cost of cargo handling based on the routine terminal approach recorded different average costs per ton of cargo per year, the total average of which was extrapolated and summed up to USD 85.74 per ton. The results of the costing based on terminal (routine) approach (sample1, S_1) and that ofthe optimization approach (sample2, S_2) are presented in table 4 below.

Table 4: Costs of cargo handling: routine terminal and optimization approaches compared

Period	Dry & liquid bulk cargo throughput (tons)	Routine terminal costs allocation @ \$85.74 per ton (extrapolated average/year)	Optimization costs projection @ \$79 per ton
2015	7,297,572	\$625,693,823.30	\$576,508,188.00
2016	8,758,299	\$750,936,556.30	\$691,905,621.00
2017	10,509,944	\$901,122,598.60	\$830,285,576.00
2018	12,611,932	\$1,081,347,050.00	\$996,342,628.00
2019	15,134,316	\$1,297,616,254.00	\$1,195,610,964.00
TOTAL	**54,312,063 tons**	**\$4,656,716,282.00**	**\$4,290,652,977.00**

Source: Field study based on Table 1 and terminal operator's records, 2020

The cost figures in Table 4 being of large values, their logarithmic values were obtained for computational purposesto fit the test of hypothesis:

Table 5: Log values of routine terminal costs and optimization costs

Period	Routine terminal costs S_1	Optimization costs S_2
2015	8.80	8.76
2016	8.88	8.84
2017	8.95	8.92
2018	9.03	9.00
2019	9.11	9.08
Total (N=5)	**44.77**	**44.60**
Mean of the approaches	$\mu_1 = 8.95$	$\mu_2 = 8.92$
Standard deviation of the approaches	$\sigma^2_1 = 0.1219$	$\sigma^2_2 = 0.1265$

Hypothesis

There is no significant difference between the routine approach and the optimization approach to minimizing terminal operational costs.

The mathematical notation of the null and alternative hypothesis is given as:

$$H0: \mu \sum_1 S = \sum_2 S$$
$$H1: \mu \sum_1 S \neq \sum_2 S$$

The student 't' test statistics was employed to test the difference between the mean and standard deviation of routine terminal costs (S_1) and the costs computed by optimization (S_2). The formula is given as follow:

$$t = \frac{\overline{x_1} - \overline{x_2}}{\sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}}}$$

Substituting the formula for the values obtained in table 5:

$$t = \frac{8.95 - 8.92}{\sqrt{\frac{0.1219}{5} + \frac{0.1265}{5}}}$$

$$t = \frac{0.03}{\sqrt{0.0244 + 0.0253}}$$

$t = 0.1346$ calculated

To obtain degree of freedom (df): n(a) + n(b) – 2
= 5 + 5 – 2 = 8

Hence, the t-test critical value at 95% confidence level, degree of freedom (df) 8 for a two-tailed test =**2.3060**

Observation - T-test calculated value (0.1346) is lower than t-test critical value (2.3060)

Decision Rule – The null hypothesis H_0 is accepted and the alternative hypothesis H_1 is not.

Implications for the Study

The outcome of the hypothesis indicated that the difference in cost-savings obtained from applying the linear programming optimization approach to allocate the terminal resources (factors of production) in comparison with the routine terminal approach was not statistically significant in minimizing the terminal costs of operation. Applied in retrospect therefore, optimization might have made but only an insignificant difference in the resource allocation schema, notwithstanding the fact that the raw figures (Table 4) showed difference in cost reduction in favour of the optimization approach. Reviewing the result critically, there is the tendency for the test of hypothesis to have come out significant had the years of observation been increased beyond the five years studied. This is because the larger a population of study is, the more it tends to normal and becomes more representative and reduces statistical errors (Curran-Everett, 2017). Besides, the process of extrapolating figures in the absence of operational data which this study made use of could have exposed the data to inaccuracies that impacted the final outcome.

IV. CONCLUSION

The fact that the terminal operators wanted their costs of operation cut down is not in doubt; the consistently low ship traffic to the port of study makes cost reduction expedient in order to minimize losses tied to unused capacity. The attempt to find a quantitative approach to minimize the costs saw to the deployment of the linear optimization programming method, even as the method has continued to gain popularity based on the extant port literature. As the result of this study proved the optimization method to be ineffective as a quantitative tool for minimizing costs of operation, further study of the parameters is recommended for improved results. In addition, there is need to expose the operators to training and retraining on the techniques of optimization in terminal operations management. This is with a view to assisting not just the operators (lessees) but also lessors (port authority) adopt a realistic approach to productivity benchmarks including cargo throughput, revenue generation, profit earnings and cost projections within the confines of available and functional resources in the port and terminal.

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