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Port Performance Measurement from Perspective of Users

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ABSTRACT

Measurement of overall port performance need to consider expectations of customers and stakeholders. Existing methods with different sets of assumptions suffer from limitations and give different results. The paper suggests an assumptions free method of a single value of port performance measurement from users' perspectives (PPM-UP) where dimension/scale scores are transformed to follow Normal distribution, facilitating meaningful arithmetic aggregation satisfying desirable properties. The method avoids disadvantages of existing methods and helps to assess overall performance of ports and in the relevant dimensions and compares ports across time and space using statistical tests. Quantification of responsiveness of the scale using longitudinal data helps to assess effectiveness of adopted action plans. The method also helps to find growth curve of PPM- PU of a port and can be applied for any number of dimensions or K-point items K= 2, 3, 4, 5, …….. The proposed method with wide application areas advances scholarly and helps port authorities to evaluate their performance from the port users' point of view and take the necessary actions to improve it.

1. Introduction.

Assessment of efficiency of maritime transport should consider amongst others, well-functioning efficient ports (Marley, 2020). Ports are facilitators of trade, integrators in the logistics supply chain and a channel of integration into the global economic system. A sea port is an important node of the logistics chain and its operations impact on economy and society development of a country (Tovar *et al*. 2007).

Better quality of port infrastructure helps to improve logistics performance, reduce costs (Lakshmanan, 2011), increase local and global accessibility, and opportunities to expand markets. Every ship-hour saved by ships in a port translates into benefits for ports, costs for carriers and inventory holding outlays for shippers (Thien, 2019; Sebastian, 2019). Increase in port efficiency from the 25th to the 75th percentile reduced shipping costs by 12% (Clark *et al*. 2004). Port performance measurement (PPM) is important for monitoring, achieving competitive position and managing stakeholder relationships (Ha *et al.* 2017). In fact, port is a center where large number of organizations provides different services and together creates different products (De Langen, 2008). Efficient port system with enhanced logistic abilities is a key determinant of foreign direct investment into a country (Panayides *et al.* 2015). Port inefficiencies are reflected by longer dwell time of cargo and ships, interruptions in vessel traffic clearance, protracted documentation handling, lesser handling of container per crane-hour, higher emission of GHG gases per ton of cargo, etc. (Kahyarara, 2020).

Common approaches to PPM are:

1. Relative performance using finite set of operational and financial indicators (also known as partial productivity indicators) like Physical indicators (Cargo volume, Ship traffic, Turn Around Time (TAT), Pre-Berthing Detention (PBD), Berth Occupancy, Idle time at Berth, Capacity utilization, etc.); Productivity factors (Tons per ship day, Tons per worked hour, Moves per crane hour, Tons/Moves per meter of berth length, etc.) and Financial indicators (Operating Ratio, Operating Surplus, Operating Surplus per employee, Cost per ton/TEU, etc.)

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2. Model or formula driven analytical methods to measure absolute performance reflecting joint effects of all chosen input and output variables like Best-Worst method (Rezaei, *et al.* 2018), Data Envelopment Analysis (DEA), Stochastic Frontier Analysis (SFA), Principal Component Analysis (PCA), Analytic Hierarchy Process (AHP), etc.

The first approach speaks about supply-side of performance assessment and does not bring out the demand-side reflection, which is the users' point of view. Moreover, these partial indicators can give quite misleading results as different indicators give different rankings of ports and evaluation of interactions (joint effects) of the inputs on outputs (Estache *et al.* 2002). Varying degree of interrelationships among the indicators across time and space get changed with changes in technology, modes of operations, etc. Deployment of large container ships with reduced number of port calls results in lowering the total costs of cargo handling in the sea ports and total time required for port operations (Kowalczyk, 2012). Use of only operational and financial port performance indicators (PPIs) may not be sufficient to cover wide ranging objectives of various services offered by ports and expectations of stakeholders (Beamon, 1999).

Model driven approaches to measure port performance as a composite index (CI) involve different sets of assumptions, different methods of scaling and finding weights and even non-uniform definition and computation of indicators. However, there are different types of scaling (normalization) and each has limitations. No weighting system is above criticism (Greco *et al.* 2019). To find workers in cargo operation, Tongzon (2001) considered workers under port authorities who do not participate in cargo handling as an approximation. Martin (2002) considered stevedore workers who provide their services to stevedoring firms (carry out loading and unloading to/from ships) and the port (supply workers to the stevedoring firms). Similarly, for generated income, Liu (1995) considered the amounts received from third parties related to the port services, excluding income from the sale of goods; Martínez-Budría *et al.* (1999) also used this approach to define one of the multi-output vector components for containers. Thus, different methods gave rise to different results and different ranks to ports. In addition, non-verification of the assumptions of the methods may distort the results.

There are no universally adopted tools to measure efficiency of sea ports, despite availability of wide range of indicators for port efficiency and performance (Bichou and Gray, 2004). Measurement of port efficiency are not comparable due to non-uniformity of theoretical approaches, different time-frames, diverse ports locations and activities analyzed (Gonzalez and Trujillo, 2009). Effectiveness of ports to meet expectations of customers and stakeholders are important components that need to be included in measuring performance of ports (Brooks, 2007), keeping in mind that interests of different stakeholders vary with time and can even be contradictory. Park and De (2004) mentioned customer satisfaction as part of marketability of ports. Measuring satisfaction of port users has been advocated (Pallis and Vitsounis, 2009). A framework for assessing perceptions of port users (shipping companies, shippers, etc.) on port performance was developed by Vaggelas (2019) where a "port user" implied an entity that either consumes port services, or uses port infrastructures.

Thus, there is a need for a single measure of multi-dimensional port performance measurement from the perspective of users (PPM-PU) to assess efficiency and effectiveness of ports, evaluated by different stakeholders.

The paper suggests an assumptions-free method of obtaining a single PPM-PU value for a port by converting ordinal raw scores of a questionnaire to continuous scores following Normal distribution for meaningful arithmetic averages and satisfying the following desirable properties:

P_1 : Continuous and monotonically increasing scores where a marginal increase in an indicator will increase PPM-PU

P_2 : Avoid skew and outliers (so that there is no bias for developed or under-developed ports)

P_3 : Facilitate comparisons of various ports in terms of PPM-PU or a single port at different time periods using statistical test of equality of average PPM-PU across time and space.

P_4 : Facilitate estimation of population PPM-PU of a country or region from a representative sample of ports.

P_5 : Assess progress or deterioration of PPM-PU of a port or a group of ports by longitudinal data and undertake test of significance.

2. Literature Survey.

Impact of port performance on trade has been investigated (UNCTAD 2018a; UNCTAD 2020). A 25% improvement in port efficiency might increase growth by 2%, demonstrating close relationship between port effectiveness and trade competitiveness (Booth 2018; Niselow 2018).

Traffic handled by ports is commonly used to reflect functioning of ports (UNCTAD 2018b; Lei and Bachmann 2020; USDT, 2021). Total cargo throughput of a port is a leading economic indicator (UNCTAD 2018b). Ferrari (2011) observed positive influence of port throughput on local development but, the influence was weak (elasticity < 0.05). However, cargo volume alone cannot reflect gains from trade or improvement in total factor productivity or GDP growth (Lakshmanan, 2011).

Positive relationship exists between value-added operations at ports and economic activities (Deng *et al.* 2013). Shan *et al.* (2014) found port efficiency increased growth of a country. Yeo *et al.* (2008) found that quality of port service, logistics costs, regional connectivity, hinterland condition and port accessibility contribute significantly to a port's competitiveness. Abe and Wilson (2008) studied effect of infrastructure on trade and found port efficiency was a major determinant of trade performance.

Studies to examine relationships of port efficiency with ownership status gave mixed results. For example, Notteboom *et al.* (2000) used Bayesian Stochastic Frontier Model to 36 European and four Asian container terminals and found no clear relation between the port efficiency and the ownership status (private or public owned). Based on a sample ports of UK and

South Korea, Cullinane and Song (2003), found positive relationship between the extent of private sector participation and productive efficiency of ports. Yuen *et al*. (2013) observed that foreign participation in the ownership status of Chinese ports increased efficiency of container terminals.

Ways to measure port efficiency and performance are diverse (Ducruet *et al*. 2014). While Lirn *et al.* (2003) suggested 47 criteria on attractiveness of ports; Yeo *et al*. (2011) suggested 38 components for port competitiveness considering efficiency as a proxy of competitiveness. However, concepts of performance of a port are different from its attractiveness or competitiveness. Evaluation criteria of perceptions of Port users' like satisfaction, competitiveness, effectiveness of service delivery, etc. are different constructs (Brooks et al. 2011). PPM-PU are usually done by online survey using predetermined structured questionnaire where identified dimensions are decided based on port-sea interfaces, within port area and port-land interfaces. In addition to overall performance, a port also needs to capture performance in each dimension and relative importance of the domains.

The method of Evidential Reasoning (ER) (Yang and Xu, 2002) for multi-group multi-criteria decision making (MCDM) has been applied in the context of port choice to deal with the inherent uncertainty in a MCDM structure (Yeo *et al*., 2014). But, it did not address PPIs from various stakeholders, and failed to incorporate the interdependency among PPIs. Munim and Schramm (2018) considered the following latent constructs and indicators for a structural equation model (SEM) to examine impact of port quality on trade:

1. Quality of port infrastructure (QPI): Measured by a questionnaire consisting of 6-point Likert items from 1 to 7 to assess perceptions of business executives on port facilities where "1" and "7" represents respectively extremely underdeveloped and efficient by international standards port infrastructure (http://data.worldbank.org/indicator/-IQ.WEF.PORT.XQ).
2. Logistics performance (LP): Ability to track and trace consignments; competence and quality of logistics services; ease of arranging competitively priced shipments; efficiency of customs clearance process; frequency with which shipments reach consignee within scheduled or expected time; quality of trade and transport-related infrastructure, seeking feedbacks in Likert scales from global freight forwarders and express carrier on logistics "friendliness" of the countries in which they operate (http://lpi.-worldbank.org/).
3. Seaborne trade: Container traffic ('000 TEUs); Liner shipping connectivity index (LSCI) based on five maritime transport components: number of ships handled, their container-carrying capacity, maximum vessel size, number of services, and number of companies that deploy container ships in ports of a country (http://data.worldbank-.org/indicator/IS.SHP.GCNW.XQ).
4. National economy: GDP per capita; Purchasing power parity (PPP) (Int. $)

Considering objective factors (cost, landside accessibility, draft availability) and perception-based subjective factors (reliability, preferences, and product differentiation), Tongzon & Heng (2005) proposed port-competitiveness-index (PCI). Major limitations of PCI are (i) Measuring stakeholders' perceptions in ordinal scale with limitations and difficulties in monitoring (ii) Non-consideration of financial efficiency and sustainability efficiency and (iii) Lacks appropriate method of combining ordinal data and ratio/interval scale data.

A service's reliability is deemed as the single outcome of service transactions. But, variability in logistics services by its providers serves as a determinant of logistics quality (Dua and Sinha, 2019). Thus, reliability of port services may be considered as a composite measure in a continuous evaluation platform.

The complex autoregressive distributed lag (ARDL) model was used to investigate (i) stationary, (ii) co-integration and panel ARDL estimation (Menegaki 2019). The model requires that the error terms should have no autocorrelation with each other, no heteroscedasticity in the data. In simple terms, mean and variance should remain unchanged throughout the model and data should be normally distributed. Pesaran (2007) argued that panel unit root tests can lead to spurious conclusions if they fail to take account of significant degrees of cross-section dependence.

Vaggelas (2019) used 7-point scale to capture responses from port users on their satisfaction and also on their perceived importance. Average ratings were computed for each selected indicator or criterion for satisfaction and separately for perceived importance; differences of which were taken as GAP, without addressing methodological issues like admissibility of average rating and their differences, scale quality like reliability, validity, responsiveness, etc.

3. Problems of rating scales.

Major difficulties of Likert scales to assess perceptions / preferences of stakeholders are:

- Levels like *very often, often, once in a while, almost never* and *never* could be dubious as individuals differ on frequency of an action to consider it as often. Pertinent question is how often is *often*? (Gu *et al*. 1995)
- Ordinal discrete scores of items of Rating scales are not additive as distance between successive levels is not uniform and unknown (Munshi, 2014). Equidistant property demands constant distance between two successive levels.
- Meaningful interpretation of scores of two items say $X \pm Y$ with unknown and different distributions is difficult unless we find joint distribution of $X \pm Y$. From the measurement point of view, $X + Y = Z$ is meaningful for discrete case if

$$P(Z = z) = P(X = x, Y = z - x) \quad (1)$$

and for continuous case,

$$P(Z \leq z) = P\ (X + Y \leq z) = \int_{-\infty}^{\infty} (\int_{-\infty}^{z} f_{X,Y}\,(x,\ t - x)\,dt)dx \tag{2}$$

Thus, it is necessary to know probability density function (pdf) of each variable being added and their convolution.

- Successive levels of items are not perceived as equidistant by subjects (Lee and Soutar, 2010)
- Summative scale sore assign equal importance to the items and dimensions despite showing different values of item – total correlations and factor loadings (Parkin *et al.*2010)
- Non-satisfaction of the equidistance assumption implies non-admissibility of operations like addition. The analysis need to be limited to frequencies under item- level combinations.
- Mean, Standard deviation (SD) of Rating scales with *K*-number of levels (*K*-=3, 4, 5, 6, 7 .... *)* increase as *K* increases (Finn, 1972). Different values of *K* distorts shape of distribution of scores and influence item/scale parameters like Reliability, validity, and discriminating power, more by number of levels than the underlying variable (Preston and Colman, 2000; Lim, 2007).
- Different responses to different items can generate tied score for more than one respondent. Thus, the scale fails to discriminate the respondents getting same scale score.
- Empirical distribution of item scores and test scores are different and often found to be skewed.

4. Proposed Method.

Above said problem areas can be avoided by considering weighted sum where weights based on frequency of different levels of different items (Chakrabartty, 2020) are used first to convert ordinal item score to continuous equidistant scores (*E*-scores) as follows:

Consider a scale with *m*-number of dimensions where number of items in the *j*-th dimension is n_j for *j*= 1, 2, …., *m* and each item has five levels (5-point items). Suppose, *N*-respondents have answered all the items of the scale.

Step 1: Convert ordinal item raw-scores (*X*) to continuous equidistant scores (*E*-scores) by finding different weights for different levels of different items, so that for the *i*-th item,

$5W_{i5} - 4W_{i4} = 4W_{i4} - 3W_{i3} = 3W_{i3} - 2W_{i2} = 2W_{i2} - W_{i1}$ = Constant. In other words, W_{i1}, $2W_{i2}$, $3W_{i3}$, $4W_{i4}$ and $5W_{i5}$ forms an arithmetic progression with common difference b >0.

Let frequencies of different levels of the *i*-th item are f_{i1}, f_{i2},-f_{i3}, f_{i4} and f_{i5}. Choose maximum ($f_{i\ Max}$) and minimum frequency ($f_{i.\ Min}$). Take initial weights$\omega_{ij} = \frac{f_{ij}}{N}$ and arrange $\omega'_{ij}s$ so that $\omega_{i1} < \omega_{i2} < \omega_{i3} < \omega_{i4} < \omega_{i5}$ where $\omega_{i1} = \frac{f_{i.Min}}{N}$ and $\omega_{i5} = \frac{f_{i.Max}}{N}$.

Take intermediate weight $W_{i1} = \omega_{i1}$ and find common difference b so that

$$W_{i1} + 4b = 5\mathrm{W}_{i5} \Longrightarrow b = \frac{5f_{i.Max} - f_{i.Min}}{4N}$$

Thus, $W_{i2} = \frac{\omega_{i1} + b}{2}$, $W_{i3} = \frac{\omega_{i1} + 2b}{3}$; $W_{i4} = \frac{\omega_{i1} + 3b}{4}$; and $W_{i5} = \frac{\omega_{i1} + 4b}{5}$.

Final weights are computed as $W_{ij(Final)} = \frac{W_{ij}}{\sum_{j=1}^{5} W_j}$ so that $\sum W_{ij(Final)} = 1$ and $j.W_{j(Final)} - (j-1)\,.W_{(j-1)(Final)}$ = constant, value of which will be different for different items.

E-scores as weighted sum are continuous and equidistant and can be used for any item with different number of levels. $b > 0$ ensures monotonic nature of *E*-scores of items. The situation $f_{ij} = 0$ for a particular *j*-th level of an item can be taken as zero value for scoring Likert items as weighted sum.

However, there could be other way to convert raw item scores (X) to *E*-scores. For example, weights could be based on area under $N(0,1)$ with $W_i > 0$ and $\sum_{i=1}^{5} W_i = 1$. Procedure for obtaining $W'_j s$ of an item considering area under $N(0,1)$ is illustrated in Table 1.

Table 1: Calculation of weights based on area under N (0,1).

Response Category	Proportion (p_i)	Cumulative Proportions (C_i)	Area under the standard Normal curve	Initial Weights
1	$p_1 = \frac{f_1}{mn}$	p_1	$A_1 = Upto\ \ p_1$	$\omega_1 = \frac{A_1}{\sum A_i}$
2	$p_2 = \frac{f_2}{mn}$	$p_1 + p_2$	A_2= $Up\ to\ \ p_1 + p_2$	$\omega_2 = \frac{A_2}{\sum A_i}$
3	$p_3 = \frac{f_3}{mn}$	$p_1 + p_2 + p_3$	$A_3 =\ Upto\ \ p_1 + p_2 + p_3$	$\omega_3 = \frac{A_3}{\sum A_i}$
4	$p_4 = \frac{f_4}{mn}$	$p_1 + p_2 + p_3$+p_4	$A_4 = Upto\ \ p_1 + p_2 + p_3$+$p_4$	$\omega_4 = \frac{A_4}{\sum A_i}$
5	$p_5 = \frac{f_5}{mn}$	$p_1 + p_2 + p_3$+p_4 + p_5=1.00	$A_5 = Upto\ \ p_1 + p_2 +$ p_3+$p_4 + p_5$	$\omega_5 = \frac{A_5}{\sum A_i}$
Total	1.00		$\sum_{i=1}^{5} A_i > 1$	1.00

Source: Author.

Here, $\omega_j > \omega_{j-1}$ for *j*= 2,3,4,5. Thus, the monotonic condition is satisfied. However, to make the transformed scores equidistant for a 5-point scale, divide the difference between Maximum area and the Minimum area by 3 and call it the correction factor α. Determine the modified areas $\Delta_1, \Delta_2, \Delta_3, \Delta_4$ and Δ_5 as follows:

$\Delta_1 = A_1$(unchanged), $\Delta_2 = \Delta_1 + \alpha$; $\Delta_3 = \Delta_2 + \alpha$; $\Delta_4 = \Delta_3 + \alpha$; $\Delta_5 = \Delta_4 + \alpha$

Define corrected weights $W_j = \frac{\Delta_j}{\sum_{j=1}^{5} \Delta_j}$ Transformed scores based on corrected weights so defined satisfy the monotonic condition, ensures equidistant scores and also satisfy $\sum_{j=1}^{5} W_j = 1$.

It may be noted that weights to the response-categories are different for different items for the Method based on frequency of each response - category but, weights to various response-categories remain unchanged across items in Method based on area under $N(0,1)$. Thus, the former method appears to be more rigorous and preferable.

Step 2: Standardize *E*-scores of *i*-th item as $Z_i = \frac{E_i - \overline{E_i}}{SD(E_i)}$ $\sim N(0,\ 1)$ where $-\infty \leq Z_i \leq \infty$.

Step 3: To ensure positive scores and uniformity in score–

range, transform Z_i to proposed score P_i by

$$P_i = (100 - 1)\left[\frac{Z_i - MinZ_i}{MaxZ_i - MinZ_i}\right] + 1 where 1 \le P_i \le 100 \quad (3)$$

Thus, both individual scores and item scores are in terms of expected values and hence each is continuous satisfying following conditions of linearity, for constants α and β:

E (x + y) = E(x) + E(Y)

E (αx) = αE(x)

E (αx +βy) = αE(x) +βE(y)

Normally distributed P_i−scores of the items belonging to a dimension can be added to get the Dimension scores. Sum of the dimension scores or equivalently sum of all item-wise P_i−scores will be the scale scores. Dimension scores as well as Scale scores will follow normal. If scores of the *i*-th dimension $\sim N\ (\mu_i,\ \sigma_i)$, scale scores also follow normal with mean $\sum_i \mu_i$ and variance $[\sum \sigma_i^2 + 2\sum_{i\neq j} Cov(D_i, D_j]$ which can be estimated from the data. Thus, probability density function (pdf) of scale scores as convolution of item-wise normally distributed P_i−scores can be found where parameters of the distribution can be estimated from the data

E-scores and *P*-scores consider pattern of responses unlike raw scores (*X*) and give unique ranks to the individuals. Chakrabartty and Sinha (2022) gave example of zero tied scores in *E*-scores and *P*-scores when X = 23 for each of seven persons.

4.1. Benefits of the proposed method:

1. Conversion of raw scores to normally distributed scores can be done irrespective of number of items in a dimension and number of response-category of items.
2. Possible to find dimension sores (D_i) indicating performance in the dimension and scale scores (S) reflecting overall performance of a port (PPM- PU) through better admissibility of arithmetic aggregation.
3. Dimension scores and total scores are continuous, monotonic, normally distributed and help to undertake parametric analysis including estimation of population mean (μ), population variance $\left(\sigma^2\right)$, from a representative sample of ports of a country or region. The method helps to test hypothesis of equality of means and variances like $H_0:\ \mu_1 = \mu_2$ or $H_0:\ \sigma_1^2 = \sigma_2^2$ either for longitudinal data or snap-shot data.
4. *P*-score reduces drastically number of tied scores and provide unique ranks to the ports and thus, help in better ranking of ports
5. Contribution of a dimension to PPM-PU is given by

$$Contribution_{i-th\ Dimension} = \frac{D_i}{S} \times 100 \quad (4)$$

6. Percentage progress/deterioration of the *i*-th port in *t*-th time-period over the previous year can be assessed by Percentage progress:

$$\%Progress = \frac{(PPM - PU)_{it} - (PPM - PU)_{i(t-1)}}{(PPM - PU)_{i(t-1)}} \times 100 \quad (5)$$

which quantifies responsiveness of the entire scale and effectiveness of adopted action plan. $(PPM - PU)_{it} > (PPM - PU)_{i(t-1)}$ implies progress in *t*-th period over (*t*-1)-th period. Deterioration, if any may be probed to identify the dimension(s) where deteriorations occurred and extent of deteriorations for possible corrective actions. Similarly, progress for a group of ports is reflected if

$$\overline{(PPM - PU)_{it}} > \overline{(PPM - PU)_{i(t-1)}} \quad (6)$$

7. Statistical tests of significance of progress in a dimension or PPM-PU can be tested $H_0 : \frac{D_{it} - D_{i(t-1)}}{D_{i(t-1)}} = 0$ or $H_0 : \frac{(PPM-PU)_{it} - (PPM-PU)_{i(t-1)}}{(PPM-PU)_{i(t-1)}}$ since ratio of two normally distributed variables follows χ^2 distribution
8. Plotting of progress/deterioration of a port across time helps to compare progress pattern that is, response to the corrective measures adopted from the beginning of the longitudinal study.
9. Normality helps to estimate variance of each item and variance of the scale and thus enables estimation of scale reliability by Cronbach alpha at population level.
10. Normality distributed scores satisfy the basic assumption of PCA and computation of factorial validity as $\frac{\lambda_1}{\sum \lambda_i}$, where λ_1 is the highest eigenvalue associated with the first principal component. Factorial validity reflects the main factor for which the scale was developed and accounts for $\frac{\lambda_1}{\sum \lambda_i} \times 100$ percent of overall variability. Such factorial validity from single administration of a test avoids the problems of construct validity and is independent of criterion scale (Parkerson, *et al.* 2013).

5. Discussion.

Dimensions-wise performance of ports goes beyond handling operations at the berths and terminal areas. However, selection of dimensions and items within a dimension need to be decided keeping in mind multi-dimensional nature of port performance, considering changing roles of the ports to its customers and stakeholders, global competition replacing local competitions, adaptation of market economies which demand lowering costs including logistics cost, induction of technology in navigability and loading and discharging process, role played as a node in supply – change management, Rail – Road – IWT connectivity and Dry Port interfaces, environmental and climate related issues, etc. If needed, corporate social responsibility (CSR) on ports can be added as additional dimension. It can be assumed that ports are continuously trying to measure and improve their performances in the selected dimensions. In short, dimensions of the port performance need to bring a well-fitted perception to the modern port performance concept.

Items within a dimension can be selected by pilot study where a large pool of items is administered to a group of expert stakeholders, ensuring that choice of higher response-category implies better performance. Heuristic approach may be used to delete the items in stages where (i) agreement≤ 25 per cent implying ambiguity or difficulty to understand (ii) agreement in one response-category≥70 per cent since such items had poor discriminating abilities (iii) increase in Cronbach's alpha with addition of the item. In other words, delete the *j*-th item if $\alpha_j \geq \alpha_{j-1}$ where α_j denotes reliability of the dimension (sub-test) with *j*-items and α_{j-1} denotes reliability of the sub-test with (*j*-1) items. If deletion of an item increases alpha of the sub-test, the item needs to be deleted from the questionnaire.

Responsiveness of the scale is quantified by value of progress / decline of one port or a group of ports by $\frac{P_{i_{t_{j+1}}}}{P_{i_{t_j}}}$ or equivalently by $\frac{P_{i_{t_{j+1}}} - P_{i_{t_j}}}{P_{i_{t_j}}} \times 100$. Each can take positive or negative value depending on $P_{i_{t_{j+1}}} > P_{i_{t_j}}$ or $P_{i_{t_{j+1}}} < P_{i_{t_j}}$. Significance of progress or deterioration can be tested statistically since ratio of two normally distributed variable follows χ^2 distribution.

Relative importance of the dimensions to influence the scale scores is essentially the effect of small change in *i*-th dimension (D_i) to scale score (P_{Scale}) and can be quantified in terms of elasticity that is percentage change of P_{Scale} due to small change inD_i. The dimensions can be ranked based on such dimension-wise elasticity. Elasticity studies in reliability engineering, economics often consider model like $logQ_{jt} = \alpha_j + \beta_j logP_{jt}$ where Q_{jt} denotes the quantity demanded of *j*-th industry at time *t* and P_{jt} is industry price relative to the price index of the economy. However, for *P*-scores following normal, logarithmic transformations are not required to fit regression equation of the form $P_{Scale} = \alpha_i + \beta_i D_i + \varepsilon_i$ where $\beta_i = r_{P_{Scale},\, D_i} \left[\frac{SD(P_{Scale})}{SD(D_i)}\right]$. The coefficient β_i reflects the impact of a unit change in the independent variable (*i*-th dimension) on the dependent variable (P_{Scale}). However, these coefficients are not elasticity's. Convention of a meaningful estimate of elasticity is to consider it at the point of means, since all regression lines pass through the point of means. Elasticity of the independent variable D_i for a regression equation of P_{Scale} on $D_i's$, can be written as $\frac{\frac{\Delta P_{Scale}}{P_{Scale}}}{\frac{\Delta D_i}{D_i}} = \frac{\Delta P_{Scale}}{\Delta D_i}\frac{D_i}{P_{Scale}} = \beta_i \frac{D_i}{P_{Scale}}$ where β is the slope of regression line $Q = \alpha + \sum \beta_i D_i$. Thus, elasticity of the *i*-th dimension $e_i = \beta_i \frac{Mean\ (D_i)}{Mean(P_{Scale})}$. The dimensions can be arranged by increasing order of elasticity (e_i). Policy makers can decide appropriate actions in terms of continuation of efforts towards the dimensions with high values of elasticity and corrective actions for the dimensions with lower elasticity that is, areas of concern. However, high correlation between a pair of dimensions indicates presence of multicolinearity which indicates overlapping between the two dimensions and may not be desirable. PCA or FA may result in lesser number of independent factors than the number of dimensions considered since some of the dimensions may be correlated.

Conclusions

The paper suggests a simple assumptions free method of obtaining a single PPM - PU value for a port considering multi-criteria goals, and relevant components by converting ordinal raw scores of items of a questionnaire to continuous scores following Normal distribution for meaningful arithmetic averages and satisfaction of desirable properties. The method helps the port planners to know overall performance of ports from the users' point of view along with performances in the relevant dimensions and compare the ports across time and space using statistical tests. Quantification of responsiveness of the scale using longitudinal data helps to assess effectiveness of adopted action plans.

The proposed method avoids disadvantages of existing methods which are either not methodologically sound or involve assumptions, verification of which are required before application of the methods. The method helps to find the growth curve of PPM- PU of a port, which in turn provides another criterion for comparison among ports. The method can be applied even for skewed raw data with any number of dimensions containing different number of *K*-point items *K*= 2, 3, 4, 5 . . . However, the proposed method requires careful preparation of the scale covering dimensions and items within a dimension.

The proposed method with wide application areas satisfying desired properties advances scholarly and the proposed method could help port authorities to evaluate their performance from the port users' point of view and take the necessary actions to improve it. Future empirical studies may be undertaken with additional sustainable sub-indicators like emission per ton cargo handled and energy consumed per ton cargo handled to prescribe effective and implementable standards for improving PPM-PU and indication of impact if the prescribed measures are implemented.

References.

Abe, K., and J. S.Wilson (2008): Trade, Transparency, and Welfare in the Asia Pacific. *Journal of International Economic Studies* 12: 35–87.

Beamon, B.M.(1999): Measuring supply chain performance. *International Journal of Operations & Production Management*, 19(3), 275-292.

Bichou and Gray (2004): A Logistics and Supply Chain Management Approach to Port Performance Measurement, *Maritime Policy and Management*. 31(1), 47-67.

Booth, L. (2018): Ports Critical for Growth in Africa. Retrieved from: https://www.commercialriskonline.com/ports-critical-growth-africa/.

Brooks, M.R. (2007): Issues in measuring port devolution program performance: a managerial.

Perspective, in Brooks, M.R. and Cullinane, K. (Eds), *Devolution, port governance and port performance,* Elsevier, London, 599-629.

Brooks, M.R., Schellinck, T. and Pallis, A.A. (2011): A systematic approach for evaluating port Effectiveness. *Maritime Policy and Management*, 38(3), 315-334.

Chakrabartty, SN and Sinha, D (2022): Assessing a Country's Sector-specific Logistics Performance: The case of India's Marine-product Sector. Under publication - Journal of Maritime Logistic.

Chakrabartty, Satyendra Nath (2020): Reliability of Test Battery. *Methodological Innovations*, 1–8. DOI: 10.1177/2059-799120918340.

Clark, X., D. Dollar, and A. Micco (2004): Port efficiency, maritime transport costs, and bilateral trade. *Journal of Development Economics* 75: 417–50.

Cullinane, K. P.B. and Song, D. W. (2003): A stochastic frontier model of the productive efficiency of Korean container terminals. *Appl. Econ.*, 35: 251–267.

Deng, P., S. Lu, and H. Xiao (2013): Evaluation of the relevance measure between ports and regional economy using structural equation modeling. *Transport Policy* 27: 123–33.

De Langen, P.W. (2008): Port performance indicators, ESPO Conference, Bilbao.

Dua, A., & Sinha, D. (2019): Assessment of quality of multimodal transportation for containerized exports. *IIM Kozhikode Society & Management Review*, 8(1), 10-22.

Ducruet, C., H. Itoh, and O. Merk (2014): Time Efficiency at World Container Ports. http://www.internationaltransportforum.org/jtrc/DiscussionPapers/DP201408.pdf

Estache, Antonio & Trujillo, Lourdes & González, María. (2002): Efficiency Gains from Port Reform and the Potential for Yardstick Competition: Lessons from Mexico. *World Development.* 30. 545-560. 10.1016/S0305-750X(1)00129-2.

Ferrari, Claudio (2011): Ports and regional economic development: Global Ports and Urban Development: Challenges and Opportunities, OECD, Paris

Finn, R.H. (1972): Effects of some variations in rating scale characteristics on the means and reliabilities of ratings. *Educational and Psychological Measurement*, 32(7), 255–265.

Gonzalez, MM. and Trujillo, L.(2009): Efficiency measurement in the port industry: a survey of the empirical evidence, *Journal of Transport Economics and Policy,* 43, 157-192.

Greco, S., Ishizaka, A., Tasiou, M. and Torrisi, G. (2019): On the Methodological Framework of Composite Indices: A Review of the Issues of Weighting, Aggregation and Robustness, *Soc Indic Res.* 141:61–94 10.1007/s11205-017-1832-9.

Gu, Y, Wen, Q and Wu, D.(1995): How Often Is Often? *English Language Teaching;* 5, 19-35

Ha, M. H., & Yang, Z. (2017): Comparative analysis of port performance indicators: Independency and interdependency. *Transportation Research Part A: Policy and Practice*, 103, 264-278.

Kahyarara, G.(2020): Investment in Port Infrastructures across Africa Coastlines. Retrieved from: https://allafrica.com/stories/202008 260455.html

Kowalczyk, Urszula (2012): Case Study on Hub - And - Hinterland Development In The Baltic Sea Region, Maritime Institute in Gdansk, TransBaltic Project, Gdansk, Poland 2012

Lakshmanan T (2011): The broader economic consequences of transport infrastructure investments. *J Transp Geogr* 19(1): 1–12.

Lee JA and Soutar G. (2010): Is Schwartz's value survey an interval scale and does it really matter? *J Cross-Cultural Psychol*; 41: 76–86.

Lei, C., and Bachmann, Q. (2020): Assessing the role of port efficiency as a determinant of maritime transport costs: Evidence from Canada. *Maritime Economics & Logistics* 22: 562–84.

Lim, Hock-Eam (2007): The Use of Different Happiness Rating Scales: Bias and Comparison Problem? *Soc Indic Res.* 87:259–267.

Lirn, T. C., Thanopoulou, H.A. and Beresford, A. K. C. (2003): Transshipment port selection and decision making behavior: analyzing the Taiwanese case, *International Journal of Logistics,* 6(4), 229-244.

Liu, Z. (1995): The comparative performance of public and private enterprises. *Journal of Transport Economics and Policy*, 29:263-274.

Marleny, A. (2020): UNCTAD says Maritime Transport of Goods Helps Minimise Covid-19 Economic Impacts. Retrieved from: https://www.engineeringnews.co.za/article/unctad-says-maritime-transport-of-goods-help-minimise-covid-19-economic-impacts-2020-03-26.

Martín, M. (2002): El sistema portuario español: regulación, entorno competitivo y resultados. Una aplicación del análisis envolvente de datos, Ph.D. Thesis, Universitat Rovira I Virgili.

Martinez-Budria, E., Diaz-Armas, R., Navarro-Ibafiez, M. and Ravelo-Mesa, T. (1999): A study of the efficiency of Spanish port authorities using data envelopment analysis. *International Journal of Transport Economics*, 2:237-253.

Menegaki, A. N. (2019): The ARDL Method in the Energy-Growth Nexus Field; Best Implementation Strategies. *Economies* 7: 105.

Munim, Z. H., and H. Schramm (2018): The Impacts of Port Infrastructure and Logistics Performance on Economic Growth: The Mediating Role of Seaborne Trade. Retrieved from: https://-jshippingandtrade.springeropen.com/articles/10.1186/s41072-0 18-0027-0.

Munshi, Jamal (2014): A Method for Constructing Likert Scales. *SSRN Electronic Journal*. 10.2139/ssrn.2419366.

Niselow, T. (2018): Port of Durban Likely to Emerge as One of Africa's Major Hubs-PwC. Retrieved from: https://www.fin24-.com/Economy/port-of-durban-likely-to-emerge-as-one-of-africas-majorhubs-pwc-20180413.

Notteboom, T., Coeck, C. and Van Den Broeck, V. (2000): Measuring and explaining the relative efficiency of container terminals by means of Bayesian stochastic frontier models, *International Journal of Maritime Economics*, 2(2), 83-106.

Pallis, AA. and Vitsounis, TK. (2009): Port performance: measuring port users' perspectives, WCTR Conference – Special Interest Group 2, University of Antwerp.

Panayides PM, Parola F, Lam JSL (2015): The effect of institutional factors on public–private partnership success in ports. *Transp Res A Policy Pract* 71:110–127.

Park, RK and De, PF (2004): An alternative approach to efficiency measurement of Seaports, *Maritime Economics and Logistics*, 6, 53–69.

Parkerson HA, Noel M, Pagé MG, Fuss S, Katz J, Asmundson GJ (2013): Factorial Validity of the English Language Version of the Pain Catastrophizing Scale Child Version, *The Journal of Pain,* 14(11), 1383-1389, https://doi.org/10.1016/j.jpain.-2013.06.004.

Parkin D, Rice N, Devlin N.(2010): Statistical analysis of EQ-5D profiles: does the use value sets bias inferences? *Med Decis Making* 30(5):556–565.

Pesaran, M. H. (2007): A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics* 22: 265–312.

Preston, CC and Colman, AM. (2000): Optimal number of response categories in rating scales: reliability, validity, discriminating power, and respondent preferences, *Acta Psychologica,* 104, 1-15.

Rezaei J, Palthe LVW, Tavasszy L, Wiegmans B, Laan FVD. (2018): Port performance measurement in the context of port choice: an MCDA approach. *Management Decision*, 57(2), 396-417. 10.1108/MD-04-2018-0482.

Shan, J., M. Yu, and C. Lee (2014): An empirical investigation of the seaport's economic impact: Evidence from major ports in China. *Transportation Research Part E* 69: 41–53.

Sebastian, B. (2019): Data Supporting Swifter Shipping. https://www.marinetraffic.com/blog/data-supporting-swifter-shipping/.

Thien, D.(2019): Digital Ports Way of the Future. Retrieved from: http://www.dailyexpress.com.my/news/142467/digital-ports-wayof-the-future/.

Tongzon, J. (2001): Efficiency measurement of selected Australian and other international ports using DEA. *Transportation Research Part A*, 35:113-128.

Tongzon, J., & Heng, W. (2005): Port privatization, efficiency and competitiveness: Some empirical evidence from container ports (terminals).*Transportation Research Part A: Policy and Practice*, 39(5), 405-424.

Tovar, Beatriz; Jara-Díaz, Sergio and Trujillo, Lourdes (2007): Econometric estimation of scale and scope economies within the Port Sector: a review, *Maritime Policy & Management,* 34:3, 203-223, DOI: 10.1080/03088830701342932

UNCTAD (2020): Review of Maritime Transport, New York Highlights and Figures on Africa. Retrieved from: https://unctad-.org/system/files/official-document/rmt2020_en.pdf

UNCTAD (2018a): Maritime Trade and Africa. Retrieved from: https://unctad.org/pressmaterial/maritime-trade-and-africa.

UNCTAD (2018b): Review of Maritime Transport Retrieved from: https://unctad.org/system/files/official-document/rmt2018-ch4_en.pdf

United States Department of Transportation (2021): Measures of Throughput and Capacity. Retrieved from: https://www.-bts.gov/archive/publications

Vaggelas, George K. (2019): Measurement of port performance from users' perspective. *Maritime Business Review*; 4 (2); 130-150. DOI 10.1108/MABR-08-2018-0024

Yang, J.B., Xu, D.L. (2002): On the evidential reasoning algorithm for multiattribute decision analysis under uncertainty. *IEEE Transactions on Systems, Man, and Cybernetics Part A: Systems and Humans* 32(3), 289–304.

Yeo, Gi-Tae; Ng, A.K.Y., Lee. PTW & Yang. Z. (2014): Modelling port choice in an uncertain environment, *Maritime Policy & Management*, 41:3, 251-267. DOI: 10.1080/03088839.-2013.839515

Yeo, G.T., Roe, M. and Dinwoodie, J. (2011): Measuring the competitiveness of container ports: logisticians perspectives, *European Journal of Marketing*, 45(3), 455-470.

Yeo, G. T., M. Roe, and J. Dinwoodie (2008): Evaluating the competitiveness of container ports in Korea and China. *Transportation Research Part A: Policy and Practice* 42: 910–21.

Yuen, A.C.L., Zhang, A. and Cheung, W. (2013): Foreign participation and competition: a way to improve the container port efficiency in China? *Transportation Research Part A*, Vol. 49, 220-231.