Technical Efficiency of Water Boards in South Africa: A Costing and Pricing Benchmarking Exercise

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Abstract

South Africa is a water scarce country with deteriorating water resources quantity, quality and security, infrastructure investment and management. 89 per cent of households have access to water supply, but only 64 per cent or 10.3 million households are estimated to have reliable water supply. The water sector in South Africa is cost-intensive with various monopolistic utilities. The sector is faced with weakening financial viability due to: inefficient operations coupled with inadequate investment, financing and under-pricing. As a result, cost recovery is not being achieved. To ensure the use of efficient water purification and distribution production technologies, it is important to benchmark technical efficiency. There is an urgent need for realising operational efficiency through cost reductions and improved revenue generation.

In this paper, we make use of a non-parametric method known as Data Envelopment Analysis (DEA) to analyse the technical efficiency of the 9 water boards. We achieve this objective by using data on costs, water losses, bulk sales volumes and tariffs to model the industry's technical efficiency frontiers. The study finds the mean technical efficiency scores of 73.2, 83.7, 85.8 and 92.3 per cent, in the four models respectively. This shows that on average, not all water boards were efficient and some operated below the optimal efficiency frontiers. They needed to improve their efficiency rates by 26.8, 16.3, 14.2 and 7.7 per cent respectively. To be specific, of the 9 sampled water boards, Overberg, Rand and Umgeni water boards were technically efficient in Model 1. In this model, 7 entities are operating under increasing returns to scale (IRS). In Model 2, the same water boards and Mhlathuze Water emerged efficient. Model 2 captured water losses as an input, resulting in technical efficiency scores increasing from 73.2 to 83.7 per cent. Therefore, this water supply infrastructure quality variable has a major impact on the technical efficiency of water boards. In Model 3, Amatola, Overberg, Rand and Umgeni water boards were on the optimal efficiency frontier. They were relatively efficient in maximising water sales volumes and charging bulk water tariffs at prevailing levels of expenditure. Most water boards operated under decreasing returns to scale (DRS) in this frontier. Model 4 excluded Rand and Umgeni water boards, in this model Amatola, Overberg, Magalies and Sedibeng were efficient. 4 water boards were under DRS.

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1. Introduction

Masindi and Duncker (2016) reported that South Africa is a water scarce country. The Department of Water and Sanitation – DWS (2019) added that the country is facing a water crisis caused by insufficient water resources, poor infrastructure maintenance and investment. This crisis is already having significant impacts on socio-economic objectives. Therefore, it is critical for water resources to be managed efficiently. The water sector value chain is comprised of water resources, bulk and retail water and sanitation services. According to Masindi and Duncker (2016), the DWS is the custodian of water resources, it leads policy development and regulates the water and sanitation sector in South Africa. The DWS manages water resources by planning and implementing large water resources infrastructure projects, issuing water use licenses, allocating water, performing catchment management functions, river systems management, water storage and abstraction and return-flow management.

According to the DWS (2019), the national annual runoff is approximately 49 000 million m^3/a giving a reliable yield of surface water, at an acceptable assurance of supply at 98 per cent of 10 200 million m^3/a. There are more than 5 511 registered dams in South Africa (DWS 2018). According to the DWS (2018), the water boards, DWS, municipalities and other state departments own about 854 dams, mostly with high storage capacity and the private sector owns about 4 657 dams. The mines, industries and businesses own approximately 335 dams and agriculture has 4 322 dams, most of which have small storage capacity. The total gross storage capacity of registered dams was approximately 33 292 million m^3 (i.e. 33 292 gigalitres). Ground water potential was 7 500 million m^3/a, with only 50 per cent currently in use. The quality of rivers and ground water remains poor, signalling weaknesses in water resources management. In terms of water use, the DWS (2019) reported that agriculture used 61 per cent of allocated water while municipalities use 27 per cent. The remainder was attributable to other sectors, such as energy, industries, mining, livestock and forestry.

According to Masindi and Duncker (2016), there are 9 water boards mainly responsible for bulk water purification and distribution, however, some municipalities and the DWS also perform this function. The National Treasury (2019) stated that water boards are mandated by the Water Services Act to provide bulk industrial and potable water services to municipalities and industries within their legislated areas of supply. The water boards vary in size, activities, customer mix, revenue base and operational capacity. The National Treasury (2020, 2019, 2018) indicated that over a 5-year period (2015-2019), on average, the consolidated water boards' bulk potable water supply volumes were 2 528 million m^3 or 2.528 gigalitres per annum, charged at varying levels of bulk water tariffs. Rand Water accounted for 65 per cent of total volumes and Umgeni Water accounted for 17 per cent.

According to National Treasury (2020, 2019, 2018), the same trends are found in revenue and expenditure, with Rand Water accounting for 62 per cent of total average expenditure of R16.2 billion and Umgeni Water for 12 per cent over the 5-year period. To improve reliable and clean water supply, the water boards invested on average, R5 billion on bulk water and sanitation infrastructure over the same period. The water boards purchased most of their raw water from the DWS. These entities treat the raw water at their water treatment plants (WTWs) for distribution to their customers (largely the 143 municipalities).

In terms of the Constitution, municipalities have sole powers to reticulate water to households, however where there is no capacity to deliver, they appoint other service providers to perform the function on their behalf. The bulk distribution networks of water boards are generally in good condition, with acceptable levels of water losses, showing good management of infrastructure. However, water losses are higher for some water boards relative to peers, needing immediate attention. On the other hand, the DWS (2019) indicated that approximately 56 per cent of over 1 150 municipal wastewater treatment works (WWTWs) and approximately 44 per cent of 962 WTWs in the country are in a poor or critical condition, and 11 per cent of this infrastructure is completely dysfunctional. Despite this, the country has 89 per cent of households with access to water supply infrastructure, however, only 10.3 million people (64 per cent of households) are estimated to have a reliable water supply service. Therefore, most challenges in the water sector are prevalent in the water resources and retail space.

Masindi and Duncker (2016) and DWS (2019), indicated that some challenges facing water boards, municipalities and the DWS, include weak governance, lack of adequate funding coupled with inefficient operations to meet and sustain investment requirements, inappropriate financing and pricing arrangements and lack of accountability. Moreover, water is severely under-priced and cost recovery is not being achieved. This results in ineffective operations and maintenance of water supply infrastructure. Gupta, et al. (2012) advised that if the revenue generated from user charges falls short of the expenditure made for the supply of water, the consequence is deteriorating assets and weak financial sustainability of services. According to the DWS (2019), to achieve water security an estimated capital funding gap of around R33 billion per annum is needed for the next 10 years. This must be achieved through a combination of improved revenue generation, a significant reduction in costs and operational efficiencies.

Just restating the aforementioned problems is not helpful, a solution is needed. The aim of the study is to benchmark the production technologies of the water boards in South Africa to determine potential efficiency improvements. There are many water sector technical efficiency benchmarking studies across globe, including on municipalities in South Africa. However, we did not find any study that examined the efficiency of South African water boards from a technical and operational efficiency perspectives (in particular costing and pricing). This innovative paper fills this gap in the literature by applying a non-parametric benchmarking tool known as Data Envelopment Analysis (DEA) to compare the efficiency of productive units (9 water boards in this case). This is achieved by scientifically analysing data related to the resources used by the water boards and the outcomes they achieve during the study period. DEA enables us to analyse the technical efficiencies of water boards with respect to water loss management, bulk water costing and pricing using data from 2014/15 to 2018/19. This provides an opportunity for policy makers to determine how well a particular water board is performing relative to its peers, to identify good and bad practices, and finally find more efficient approaches to achieve financial sustainability and reliable water supply.

In scenario 1, we find that the average technical efficiency score of the 9 water boards is 73.2 per cent. The score is 83.7 per cent in scenario 2, 85.8 per cent in scenario 3 and 92.3 per cent in scenario 4. This reflects that not all water boards were operating on the efficiency frontiers. The inefficient water boards needed to improve technical efficiency by 26.8, 16.3, 14.2 and 7.7 per cent respectively in the four scenarios. Specifically, in Model 1, only 3 water boards were efficient, 4 boards were efficient in Models 2, 3 and 4 respectively. That is, in Models 1 and 2, the efficient water boards used optimal levels of personnel, expenditure while maintaining appropriate levels of water losses at prevailing output levels (volumes sold). In Models 3 and 4, the efficient water boards are maximising water sales volumes and charging bulk water tariffs at prevailing levels of expenditure.

The rest of the paper is organised as follows: Section 2 deals with the literature, Section 3 with methodological specification, Section 4 with the data, Section 5 with the results and Section 6 concludes the study.

2. Literature review

As stated above, DEA has been extensively used globally to analyse technical efficiency in the water sector. However, to the best of our knowledge, this is the maiden study to use DEA or any other modelling technique to analyse the efficiency of water boards in South Africa. In regards to the water sector efficiency literature, Ali, et al. (2018) used the constant returns to scale (CRS) along with an input-minimisation DEA to analyse the performance of 4 water supply units in Pakistan over a three-year period (2013-2015). The study adopted a six-variable production technology consisting of two outputs (number of consumers served and revenue) and four inputs (management, maintenance, operations and energy costs). They found that only 3 units were efficient. The average technical efficiency scores of 89, 92 and 97 per cent were respectively observed for the three years. Lannier and Porcher (2014) used an input-minimisation DEA based on the variable returns to scale (VRS) in stage 1 and a Stochastic Frontier Analysis (SFA) in stages 2 and 3. They assessed the relative technical efficiency of 177 water supply decision making units (DMUs) in France. Revenue was used as a proxy for costs. The volume of billed water, number of customers and length of water pipes were used as outputs. Network performance was included as a quality output. They found that private utilities were on average slightly less efficient than public utilities due to difference in resource management. The first-stage, DEA yielded an average technical efficiency score of 75.4 per cent and 84.1 per cent. After factoring the environmental variables, the public management scores were on average 0.88 while the private management scores were 0.82. The third stage DEA yielded average technical efficiency scores of 90 per cent.

Kulshresthaa and Vishwakarma (2013) used a DEA model to determine the water supply efficiency of 20 urban municipalities in the state of Madhya Pradesh, in India. Three input-oriented DEA models were used in efficiency evaluation. Each model had three outputs (number of connections, length of distribution network and average daily water production), while the number of inputs varied from one to three (staff per 1000 connections, operating expenditure and non-revenue water) consecutively in each model. The results of the analysis indicated significant inefficiencies amongst various municipalities that supply water. It was found that larger cities exhibited better efficiencies than the smaller ones. The average technical efficiency score in Model 1 was 49 per cent with the highest score of 83 per cent observed in Model 3. Alsharif, et al. (2008) used DEA to measure the technical efficiency of 33 Palestinian municipalities for the years, 1999–2002. They found that the Gaza Strip efficiency scores were considerably lower than those of the West Bank. Water losses were the major source of the inefficiency, indicated by the large slacks on this input. Another study by Gupta, et al. (2012) applied an output-oriented DEA to assess the productive efficiency of urban water supply systems in 27 selected Indian cities. The study used expenditure as an input and total water served by a water utility as a function of revenue, expenditure and water production capacity. Two cities were efficient under the CRS while 6 reached the efficiency frontier under the VRS. The efficiency results had implications for urban domestic water pricing. Most water utilities were operating under decreasing returns to scale (DRS), implying that water should be priced at a marginal cost of supply.

Singh, et al. (2014) applied DEA to determine the relative efficiency of 12 selected Indian urban water utilities (municipal bodies) of Maharashtra state/province. They used an input-oriented CRS DEA model with total expenditure and staff size as two inputs and water supplied and the number of connections as two outputs. Only a third of the DMUs were efficient. Marques, et al. (2014) applied DEA to 5,538 observations of 1,144 utilities that supplied drinking water between 2004 and 2007 in Japan. The models considered three inputs and two outputs. The inputs included capital, staff, and other operational expenditures. For outputs, the volume of water and the number of customers were adopted. They found that the average level of inefficiency (weighted by volume) was 57 per cent in the CRS model, but only 24 per cent for the VRS model. Lombardi, et al. (2019) used DEA to determine the efficiency of a selected sample of 68 Italian water utility companies from 2011 to 2013. The study used water distributed percentage of the water delivery network length as an output. The cost of material, services, leases and capital were used as inputs. Under the output-oriented models, the mean technical efficiency score was 0.85 under the VRS and 0.65 under the CRS. From an input-minimisation perspective, the scores were 0.74 and 0.63 respectively for the VRS and the CRS.

As it pertains to South Africa, Brettenny and Sharp (2016) studied the efficiency of 88 authorised water services local and metropolitan municipalities. The paper used an input-oriented DEA with operating costs and system input volume as sole input and output variables. Of the 44 urban water services authorities, 10 were efficient under the VRS and 4 under the CRS. Of the rural water services authorities, 5 were efficient under the VRS and only 1 under the CRS. The performances yielded an average technical efficiency of 63.6 per cent for urban municipalities and 52.6 per cent for rural municipalities. This indicated that, on average, 36.4 per cent less expenditure could be used in urban municipalities and 47.4 per cent less expenditure in rural municipalities to achieve the given levels of water service delivery nationwide. Murwirapachena, et al. (2019) adopted DEA, SFA and stochastic non-parametric envelopment of data (StoNED) methods to analyse efficiency, based on cross-sectional data from 102 South African water utilities in the period 2013/14. They obtained varying results under the different methods. The study used total cost as a single input. Water output, total connections and the length of mains as outputs, with population served as an environmental output variable. The study estimated an input-oriented DEA, which assumed the VRS to deal with size variability. The maximum average efficiency scores under each method were as follows: Stoned (MM): 68.1 per cent, SFA: 66.2 per cent and DEA: 44.7 per cent for all utilities, 58.7 per cent for the big ones and 46.1 per cent for the small utilities. In another paper, Monkam (2014) used DEA and SFA to analyse the efficiency of 231 local municipalities in South Africa. The study adopted municipal operating expenditure as an input and 5 output variables: the number of consumer units receiving water, sewerage and sanitation, solid waste management and electricity and the total population per municipality. The results showed that on average, B1 and B3 category municipalities could have theoretically achieved the same level of basic services with about 16 and 80 per cent fewer resources respectively.

Mahabir (2014) used the Free Disposable Hull (FDH) technique to measure the technical efficiency of 129 municipalities in the provision of water from 2005 to 2009. The selected input was municipal expenditure per capita and the selected outputs were, access to piped water, grid electricity connections, a ventilated pit latrine and a flushable toilet and removal of solid waste at least one a week. The study concluded that over the period, 4 municipalities remained constantly efficient: Thembisile in Mpumalanga, Polokwane in Limpopo, Mangaung in the Free State and eThekwini in Kwazulu-Natal. The average technical efficiency score was 0.3 in 2005/06, peaking at 0.39 in 2007/08, and declining to 0.35 in 2008/09. This suggested that on average, municipalities in the sample could obtain the same level of output with at least 60 to 70 per cent less inputs (resources).

Dollery and Van der Westhuizen (2009) used DEA to determine the productive efficiency of 231 local municipalities and 46 district municipalities in the delivery of basic services covering the period 2006/2007. The study used 2 inputs: operating income and staff costs and 5 outputs, number of households, water, sanitation, refuse and electricity. The study determined the efficiency estimates under the CRS and the VRS; embracing output-orientated and input-orientated approaches. Under the output-orientated approach, the district municipalities were on average, only 30.5 per cent efficient under the CRS, 58 per cent efficient under the VRS and 48 per cent scale efficient. Two municipalities were operating at DRS-they were operating at a too large scale in efficiency terms. Under the input-orientated approach, the district municipalities were on average 47 per cent technically efficient in the case of the VRS and 64.1 per cent scale efficient. With regard to the returns to scale, 32 municipalities were operating under IRS, implying they were operating on a scale that was too small in efficiency terms. Only two district municipalities were operating at the optimal scale. The remaining district municipalities were operating at DRS. In terms of local municipalities, those with the highest average technical efficiency scores under the output-maximisation and input-minimisation measures for both the CRS and VRS were in Gauteng, with respective average technical efficiency scores of 67.7, 79.4, 67.7 and 76.7 per cent.

3. Modelling setup

Gupta et al. (2012) recommended the use of DEA for determining the technical efficiency of DMUs. They argued that despite other techniques such as the ordinary least square (OLS) and SFA being used in analysing the technical efficiency of the water industry, DEA is the most appropriate. The OLS technique is easy to use and simple to interpret, however, it suffers from the problem of specifying the functional form for the production technology and is unable to provide information on frontier performance. The SFA, although able to solve the latter problem by specifying a composed error term and splitting the error into two different parts as a data noise term and error due to the inefficiency, it also suffers from the problem of specifying the functional form and requires specification of the distribution patterns of the inherent error terms.

Gupta et al. (2012) stated that a DEA technique does not require the specification of either the functional form and/or the distributional form of the error term. Its major disadvantage is failure to accommodate the effects of data noise, which OLS and SFA do. DEA basically erects a production frontier consisting of most relatively technically efficient DMUs in the sample. This process generates technical efficiency measures for each unit in the sample by comparing observed values to optimal values of outputs and inputs. A score of 1, represents the best performing unit in the sample and a score of less than 1 implies that the unit is not performing as well as its efficient peers. DEA determines how much inputs could have been saved and the extent of outputs that could have been improved by inefficient DMUs by emulating the production processes of efficient DMUs.

In this paper, we use the VRS approach reported by Gavurova et al. (2017) and developed in 1984 by Banker, Charnes and Cooper to allow for consideration of scale efficiency analysis. This is called the Banker, Charnes and Cooper (BCC) model. The terminology “envelopment” in DEA refers to the ability of the efficiency production frontier to tightly enclose the production technology (input and output variables). Cooper et al. (2007) and McWilliams et al. (2005) state that DEA was developed in a microeconomic setting and applied to firms to convert inputs into outputs. However, in efficiency determination, the term “firm” is often replaced by the more encompassing DMU. DEA is an appropriate method of computing the efficiency of institutions employing multivariate production technologies. Aristovnik (2012) and Martić, et al. (2009) state that there are input-minimisation and output-maximisation DEA models. The former determines the quantity of inputs that could be curtailed without reducing the prevailing level of outputs. The latter expands the outputs of DMUs to reach the production possibility frontier while holding inputs constant. However, the selection of each orientation is study-specific.

According to Taylor and Harris (2004), DEA is a comparative efficiency measurement tool that evaluates the efficiency of homogeneous DMUs operating in similar environmental conditions, for example, DMUs dealing with bulk water supply and where the relationship between inputs and outputs is unknown. Wang and Alvi (2011) report that DEA only uses the information used in a particular study to determine efficiency and does not consider exogenous factors. DEA measures the distance of production functions by determining the radial extent of DMUs to the efficiency frontiers. It does so by categorising the DMUs into extremely efficient and inefficient performers. In terms of the DEA methodology, the current study uses the BCC model with the ratio of DMUs complying with the norms of at least being 2 to 3 times the combined number of inputs and outputs. Before explaining the BCC model, it is prudent to first describe the CRS model, developed by Farrell in 1957 and enhanced in 1978 by Charnes, Cooper and Rhodes (also called the CCR model). They converted the fractional linear efficiency estimates into linear mathematical efficiency programmes under the CRS. These models are described in the following paragraphs.

Under the CCR model, suppose there are C different number of inputs and D different number of outputs for N DMUs. These quantities are represented by column vectors xij (i = 1, 2, 3, …C, j = 1,2,3 …N) and qrj (r = 1, 2, 3, …D, j = 1,2,3 …N) The $C\ x\ N$ input matrix, X and $D\ x\ N$ output matrix, Q represents the production technology for all the N number of DMUs. For each DMU, the ratio of all the output variables over all the input variables is represented by u'qrj/v'xi. Where u $= D\ x\ 1$ vector output weights and v $= C\ x\ 1$ vector input weights. The optimal weights or the efficiency estimates are obtained by solving a mathematical problem. In the context of the CRS, an efficient DMU operates at technically optimal production scale (TOPS). Hence, the optimal weights or efficiency estimates are obtained by solving a mathematical problem that is reflected in equation 1.

Tops = $\max_{u,v}$ (u'qrj/v'xij)

$St.$

u'qrj/v'xij ≤ 1 (1)

u, v ≥ 0

Equation 1 shows the original linear programme, called the primal. It aims to maximise the efficiency score, which is represented by the ratio of all the weights of outputs to inputs, subject to the efficiency score not exceeding 1, with all inputs and outputs being positive. Equation 1, has an infinite number of solutions, if (u,v) is a solution, so is αv,αv. To avoid this, one can impose a constraint v'xij =1, which produces equation 2.

$\max_{u,v}$ ($u'q_{rj}$)

$St.$

$v'x_{ij} = 1$ (2)

$u'q_{rj} - v'x_{ij} \leq 0$

$u, v \geq 0$

An equivalent envelopment problem can be developed for the problem in equation 2, using duality in linear programming. The dual for $\max_{u,v}$ ($u'q_{rj}$) is $min\theta, \lambda\theta$. The value of θ is the efficiency score; it satisfies the condition $\theta \leq 1$; it is the scalar measure. Lauro et al. (2016) report that λ is an $NX1$ vector of all constants representing intensity variables indicating necessary combinations of efficient entities or reference units (peers) for every inefficient DMU, it limits the efficiency of each DMU to be greater than 1. This results in equation 3, which represents the CCR-CRS model with an input minimisation orientation.

$Min\theta, \lambda\theta$

$St.$

$-q_{rj} + Q\lambda \geq 0$ (3)

$\theta x_i - X\lambda \geq 0$

$\lambda \geq 0$

Avkiran (2001) states that the CRS postulates no significant relationship between DMU's operational size and their efficiency. That is, under the CRS assumption, the large DMUs are deemed to attain the same levels of efficiency as small DMUs in transforming inputs to outputs. Therefore, the CRS assumption implies that the size of a DMU is not relevant when assessing technical efficiency. However, in most cases DMUs have varying sizes and this becomes a factor when determining their efficiency. As a result, Gavurova et al. (2017) mention that in 1984, the CCR formulation was generalised to allow for the VRS. Aristovnik (2012) adds that if one cannot assume the existence of the CRS, then a VRS type of DEA is an appropriate choice for computing efficiency. Gannon (2005) advises that the VRS should be used if it is likely that the size of a DMU will have a bearing on efficiency. As such, Yawe (2014) cautions that the use of the CRS specification when the DMUs are not operating at an optimal scale results in a measure of technical efficiency which is confounded by scale effects. The solution is to use the VRS as it permits for the calculation of scale inefficiency. The VRS is comprehensive as it also captures the CRS performance results. The CRS linear programming problem can be modified to account for the VRS by adding the convexity constraint: $N1'\lambda = 1$ to equation 3, where $N1$ is a $Nx1$ vector of ones to formulate equation 4. Therefore, equations 1 to 3 represent the CRS models while equations 4 to 5 represent the VRS models with an input-minimisation orientation. The data for Models 1 and 2 of this study are fitted through equations 4 and 5.

$Min\theta, \lambda\theta$

St.

$$-q rj + Q\lambda \geq 0 \tag{4}$$

$\theta xij - X\lambda \geq 0$

$N1'\lambda = 1$

$\lambda \geq 0$

Lauro et al. (2016) and Yuan and Shan (2016) report that the CCR and the BCC models only differ in the manner the latter includes convexity constraints. Since the current model considers the VRS, the restriction $\sum_{i=1}^{n} \lambda n = 1$ is introduced. Ramírez Hassan (2008) cautions that if this restriction is not there, it would imply the application of the CRS model. The same analogy applies to all the inefficient DMUs in the sample. That is, the slacks and the radial movements are calculated for all inefficient DMUs using equation 5. The BCC is adept to calculate pure technical efficiency and inefficiency and when applied with the CCR model, it also measures scale inefficiency. Where, $\sum_{i=1}^{I} \lambda I = 1$, a DMU is on a CRS frontier, if $\sum_{i=1}^{I} \lambda I < 1$, the DMU is located on the IRS frontier and if $\sum_{i=1}^{I} \lambda I > 1$, there is DRS. Given that this study has adopted both the CCR and the VRS with an input-minimisation orientation. The DEA models used in this study also consider the slack movements for the inefficient DMUs. As a result, the models account for the slacks in equation 5.

$\text{Min } \theta, \lambda j, Sr^{+}, Si^{-}$

$$\theta - \varepsilon \left[\sum_{i=1}^{C} Si^{-} + \sum_{r=1}^{D} Si^{+} \right]$$

$St.$

$$\theta x i_0 - \sum_{j=1}^{N} xij\, \lambda j - Si^{-} = 0, \tag{5}$$

$\theta q r_0 = \sum_{j=1}^{N} qrj\, \lambda j - Sr^{+} = 0,$

$$\sum_{j=1}^{N} \lambda j = 1$$

$\lambda j, Sr^{+}, Si^{-} > 0$

Models 3 and 4 of this paper adopts a slack-based VRS model with an output-maximisation orientation. Therefore, the model is expanded to account for this in Equation 6 which represents the VRS output-maximisation orientation with no slacks; while equation 7 includes them. The improved input and output variables (X'_j, Y'_j) in equation 8, are considered as fully BCC efficient.

$Max \theta, \lambda \theta$

St.

$$-qrj + Q\lambda \geq 0 \tag{6}$$

$\theta xij - X\lambda \geq 0$

$N1'\lambda = 1$

$\lambda \geq 0$

$\text{Max}\ \theta, \lambda j, Sr^{+}, Si^{-}$

$\theta + \varepsilon \left[\sum_{i=1}^{C} Si^{-} + \sum_{r=1}^{D} Si^{+} \right]$

$St.$

$$\theta xi_0 + \sum_{j=1}^{N} xij\, \lambda j + Si^{-} = 0, \tag{7}$$

$\theta qr_0 = \sum_{j=1}^{N} qrj\, \lambda j - Sr^{+} = 0,$

$\sum_{j=1}^{N} \lambda j = 1$

$\lambda j, Sr^{+}, Si^{-} > 0$

$$X'j = Xj - s- \tag{8}$$

$Y'j = \theta\, Yj + sr^{+}$

Coelli et al. (2005) define slacks as input excesses and output shortfalls that are required over and above the initial radial movements to push DMUs to efficiency levels. Both the slack and radial movements are associated only with the inefficient DMUs. The radial movements are initial input contractions or output expansions that are required for a firm to become efficient. Si^{+} and Si^{-} in equation 5 are the output and input slacks respectively to be calculated with $\theta,$ and $\lambda n.$ ε, is the non-Archimedean constant. Gavurova et al. (2017) hint that if the slack variables of a DMU are not equal to zero and the technical efficiency score is lower than one, it is necessary to perform a non-radial shift that is expressed by the slack variables to achieve technical efficiency. In equation 5, the slack variables determine the optimum level of inputs that DMUs would have to utilise and the outputs that they would have to produce to become efficient, provided that these DMUs are inefficient. Therefore, the slacks depict the under-produced outputs or overused inputs.

4. Data

The sample of the study consists of 9 water boards for Models 1 to 3 and 7 DMUs for Model 4. The study measures the technical efficiency of water boards in using sales in bulk water volumes, personnel, water losses, total expenditure and tariffs across the four models (Table 1). There is a 99 per cent positive correlation between all input and output variables, except for tariffs (proxy of revenue) and total expenditure where the correlation coefficient is 30 per cent and for volumes sold and water losses (a proxy of cost incurred and not recovered) is -48 per cent. In this study, we follow Kulshresthaa and Vishwakarma (2013) and Alsharif, et al. (2008) in using water losses as an input. Picazo-Tadeo, et. al 2007 advised that omitting quality variables such as water losses might offer a biased picture of performance. Data for Models 1 and 2 are based on a 5-year average from 2014/15 to 2018/19. Data for Models 3 and 4 are based on a 2-year average from 2017/18 to 2018/19 due to missing values in earlier years for the bulk water tariffs for some water boards. The data for Model 4 are similar to Model 3, except that Rand and Umgeni water boards are excluded from Model 4. Our study uses an input-minimisation VRS DEA for Models 1 and 2 and the output-maximisation DEA for Models 3 and 4.

Table 1: Analytical variables and data

	Model 1			Model 2		Models 3 and 4		
Water Board	Volumes sold (ML/pa)	Personnel numbers	Water losses (%)	Volumes sold (ML/pa)	Total expenditure (R'000)	Volumes sold (ML/pa)	Tariffs (R/kl)	Total expenditure (R'000)
Amatola	32 733	458	12	32 733	417 805	31 820	11	459 773
Bloem	81 141	357	9	81 141	639 829	79 528	8	764 629
Lepelle	90 054	464	5	90 054	626 799	91 627	6	689 588
Magalies	86 027	293	6	86 027	484 741	91 458	7	574 320
Mhlathuze	45 208	264	3	45 208	590 534	44 229	4	549 716
Overberg	3 872	68	7	3 872	44 988	3 355	7	50 075
Rand	1 635 630	3 403	3	1 635 630	10 078 781	1 624 584	9	11 429 180
Sedibeng	114 074	852	9	114 074	1 389 795	120 425	9	1 544 882
Umgeni	439 706	1 106	3	439 706	1 934 871	453 185	7	2 161 570

Sources: National Treasury (2020, 2019, 2018), Amatola Water (2019, 2018, 2017, 2016, 2015), Bloem Water (2019, 2018, 2017, 2016), Lepelle Northern Water (2015), Magalies Water (2019, 2018, 2017, 2016, 2015), Mhlathuze Water (2019, 2018, 2017, 2016, 2015), Overberg Water (2019, 2019, 2017), Sedibeng Water (2019, 2017, 2016, 2015), Rand Water (2019, 2018, 2017, 2016, 2015), Umgeni Water (2019, 2018, 2017, 2016).

5. Results

The results of the efficiency analysis are reported in Table 2 and Figure 1. The mean technical efficiency score of the 9 entities is 73.2 per cent in Model 1. Only Overberg, Rand and Umgeni water boards are efficient in using the current staff levels and keeping water losses low, at prevailing levels of water volumes sold. The Sedibeng, Amatola and Mhlathuze water boards are the most inefficient in this model. On average, all the 6 inefficient water boards could improve the use of resources by 26.8 per cent. Appendix 1, shows that these water boards could reach the efficiency benchmark with 1 299 fewer personnel and could realise expenditure savings of R1.9 billion, at prevailing levels of water sales volumes per annum. Appendix 1, also shows the efficient peers from which the inefficient water boards could draw some lessons. The average technical scale efficiency score in this model is 83.7 per cent. Only Rand and Umgeni water boards operate at an optimal scale while others were on IRS (too low scale).

The mean technical efficiency rate of water boards in Model 2 is 83.7 per cent. In this scenario, Mhlathuze, Overberg, Rand and Umgeni water boards are efficient. 5 water boards are inefficient and could improve on the use of resources by 16.3 per cent. Appendix 1 shows that these entities could be fully technically efficient by realising consolidated expenditure savings of R1.2 billion, with Sedibeng Water accounting for 59 per cent. Amatola, Bloem and Sedibeng water boards have to reduce water losses by 6, 3 and 5 per cent respectively. In this model, only Umgeni and Rand water boards are operating on the most optimal scale compared to the rest. The 7 water boards on IRS have room to improve their operational scale to reach scale efficiency.

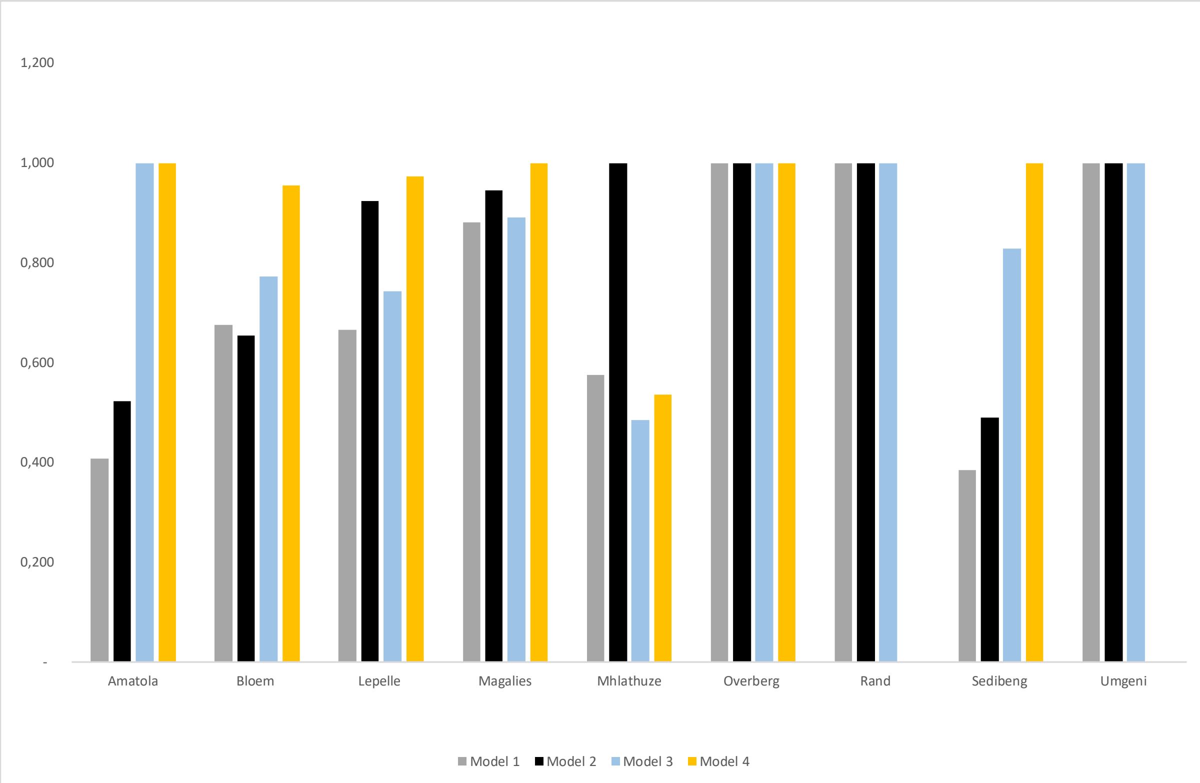
Table 2: Technical and Scale Efficiency benchmarks

Water boards	Technical Efficiency				Scale efficiency							
	Model 1	Model 2	Model 3	Model 4	Model 1		Model 2		Model 3		Model 4	
Amatola	0,408	0,522	1,000	1,000	0,850	IRS	0,665	IRS	0,449	DRS	0,524	DRS
Bloem	0,676	0,655	0,772	0,955	0,838	IRS	0,850	IRS	0,705	DRS	0,702	DRS
Lepelle	0,666	0,924	0,743	0,974	0,947	IRS	0,683	IRS	0,902	DRS	0,864	DRS
Magalies	0,881	0,946	0,891	1,000	0,885	IRS	0,825	IRS	0,905	DRS	1,000	
Mhlathuze	0,575	1,000	0,484	0,535	0,688	IRS	0,335	IRS	0,854	DRS	0,953	DRS
Overberg	1,000	1,000	1,000	1,000	0,391	IRS	0,391	IRS	1,000		1,000	
Rand	1,000	1,000	1,000		1,000		1,000		0,679	DRS		
Sedibeng	0,384	0,490	0,829	1,000	0,938	IRS	0,735	IRS	0,476	DRS	0,490	
Umgeni	1,000	1,000	1,000		1,000		1,000		1,000			
Mean	0,732	0,837	0,858	0,923	0,837		0,720		0,774		0,790	

Sources: DEA efficiency results.

The mean technical efficiency score of the 9 DMUs in Model 3 is 85.8 per cent. In this model, most water boards are close to the efficiency frontier. 4 or 44.4 per cent of the studied water boards are efficient while 5 or 55.6 are inefficient. Amatola water joined Overberg, Rand and Umgeni water boards in the most optimal technical efficiency frontier. Therefore, the current expenditure, volumes supplied and tariffs charged by these water boards are at efficient levels. The other 5 water boards have to improve productive efficiency by maximising the outputs (tariffs and volumes) at prevailing levels of expenditure. Appendix 1 reflects the necessary technical efficiency improvements. Bloem water could reach the best practice frontier by selling an additional 23 639 million m^3 per annum while increasing tariffs from R8 to R10 per kilolitre. The Lepelle Northern Water need to increase the volumes sold by 31 747 million m^3 per annum and tariffs to R8 per kilolitre. To reach the efficiency frontier, Magalies water board should increase volumes sold by 102 143 million m^3 per annum and bulk water tariffs by R1 to R8 per kilolitre. Comparatively, the Mhlathuze Water needs to increase its volumes by more than 100 per cent and tariffs by R4 to R8 per kilolitre to be technically efficient. The Sedibeng water board has to increase volumes sold by 24 779 million m^3 per annum at prevailing levels of expenditure while increasing bulk water tariffs to R11 per kilolitre. Only Umgeni and Overberg water are operating at optimal scale, the other water boards are on a DRS.

Figure 1: Technical Efficiency benchmarks



Sources: Authors' graph based on efficiency results.

In Model 4, the average technical efficiency score of the 7 small to medium-sized water boards (excluding Rand and Umgeni) is 92.3 per cent. In this model, Bloem, Lepelle Northern and Mhlathuze water boards are inefficient. Bloem water needed to improve bulk water sales by 3 779 million m^3 per annum and bulk water tariffs by R8 per kilolitre. Lepelle Northen Water could reach the efficiency frontier by selling 2 464 million m^3 per annum and increasing tariffs by R1 to R7 per kilolitre. Mhlathuze water has potential to be technically efficient by increasing sales volumes by 38 231 million m^3 per annum and bulk water tariffs by R3 to R7 per kilolitre. Amatola, Magalies, Overberg and Sedibeng water boards are at the most productive optimal scale in this model, they serve as best-practice benchmarks for the inefficient water boards.

6. Conclusions

The study analysed the technical efficiency of water boards using the input-oriented and output-oriented DEA methodologies. Model 1 recommends that the 6 inefficient water boards should review their staff composition to realise operational efficiency. They could operate with 1 299 less personnel and still be efficient while also finding spending efficiency savings of R1.8 billion, at prevailing output levels. Model 2 determined that on average, the 5 inefficient water boards should be spending R15 billion instead of R16.2 billion while Amatola, Bloem and Sedibeng water boards have to reduce water losses by 6, 3 and 5 per cent respectively. These resources could be redirected for capital outlays and expansion to address backlogs within their areas of supply. Given the pricing and operational sustainability challenges facing water boards, the results of Models 3 and 4 are extremely important. They carry a significant weight in influencing bulk water pricing reforms. In Model 3, it is observed that on average, water boards should charge an average bulk water tariff of R9 per kilolitre and R7 per kilolitre in Model 4. Therefore, the study provides basis for price or economic regulation in South Africa- a policy imperative that has eluded the sector for decades.

In Model 3, we show that Bloem, Lepelle, Magalies, Mhlathuze and Sedibeng water boards are not charging optimal bulk water tariffs and selling optimal water volumes relative to efficient peers. The average technical efficiency score in this production technology is 85.8 per cent, with these 5 water boards needing to improve efficiency by 14.2 per cent. However, Amatola, Overberg, Rand and Umgeni water boards were on the best practice frontier. They managed to reach the frontier by optimising the combination of tariffs and volumes sold, at prevailing levels of expenditure. In Model 4, we show that when sampling only the small and medium-sized water boards; only Bloem, Lepelle Northern and Mhlathuze water boards are inefficient, needing to improve relative technical efficiency by 7.7 per cent. Amatola, Magalies, Overberg and Sedibeng water boards are efficient. The study ascertained the relative and optimal average national bulk water tariffs that could be charged by the water boards' industry. The findings of the study also scientifically quantified the necessary input and output adjustments for optimal productive efficiency in the sector. Moreover, water losses were the major source of inefficiency as indicated by the large improvements in efficiency scores between Models 1 and 2. Therefore, decision makers operating in inefficient water boards should also focus on maintaining, refurbishing and rebuilding the water infrastructure networks to minimise water losses. Moreover, all the inefficient water boards identified in the study could be assisted through state or private financing to expand operations and maintain their assets; with repayment channelled through future operational efficiencies and increased tariff revenue predicted by the study. However, it is advised that the recommendations of the study should be implemented considering the feasibility and affordability of the proposed reforms. The study is constrained in several ways. It does not take into consideration other external environmental factors that could affect the efficiency of water boards such as non-payment for water services. The selection of the indicators affects the outcomes of the model. Therefore, a different set of indicators may lead to a different collection of results and analyses.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

No unauthorised publication of the paper is allowed without the consent of authors.

Availability of data and material

The datasets analysed during the current study are available from the corresponding author on reasonable request. This particularly relates to the DEA model inputs and results. Most of data sources are listed in the reference list.

Competing interests

The authors declare that they have no competing interests. The findings of the study represents the views of the author and not of the affiliated institutions.

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Appendix 1: Radials, slacks and efficient peers

Water Boards	1. Amatola	2. Bloem	3. Lepelle	4. Magalies	5. Mhlathuze	6. Overberg	7. Rand	8. Sedibeng	9. Umgeni	Total
Model 1: VRS										
Input 1: Number of employees	458	357	464	293	264	68	3 403	852	1 106	7 265
Input radial movement	(271)	(116)	(155)	(35)	(112)	-	-	(524)	-	(1 213)
Input slack movement	(50)	-	(36)	-	-	-	-	-	-	(86)
Input target	137	241	273	258	152	68	3 403	328	1 106	5 966
Input 2: Total expenditure (R'000)	418 000	640 000	627 000	485 000	590 000	45 000	10 079 000	1 390 000	1 935 000	16 209 000
Input radial movement	(247 289)	(207 401)	(209 202)	(57 590)	(250 786)	-	-	(855 620)	-	(1 827 888)
Input slack movement	-	-	-	-	(42 134)	-	-	-	-	(42 134)
Input target	170 711	432 599	417 798	427 410	297 080	45 000	10 079 000	534 380	1 935 000	14 338 978
Output 1: Volumes (ML/per year)	33 000	81 000	90 000	86 000	45 000	4 000	1 636 000	114 000	440 000	2 529 000
Output radial movement	-	-	-	-	-	-	-	-	-	-
Output slack	-	-	-	-	-	-	-	-	-	-
Output target	33 000	81 000	90 000	86 000	45 000	4 000	1 636 000	114 000	440 000	2 529 000
DMU peers	9;6	9;6;7	9;6	9;7;6	7;6	6	7	9;7;6	9	
Model 2: VRS										
Input 1: Total expenditure (R'000)	418 000	640 000	627 000	485 000	590 000	45 000	10 078 000	1 390 000	1 935 000	16 208 000
Input radial movement	(199 767)	(220 808)	(47 820)	(26 372)	-	-	-	(708 327)	-	(1 203 094)
Input slack movement	-	-	-	-	-	-	-	-	-	-
Input target	218 233	419 192	579 180	458 628	590 000	45 000	10 078 000	681 673	1 935 000	15 004 906
Input 2: Avoidable water losses (%)	12	9	5	6	3	7	3	9	3	
Input radial movement	(6)	(3)	-	-	-	-	-	(5)	-	
Input slack movement	-	-	-	-	-	-	-	-	-	
Input target	6	6	5	6	3	7	3	4	3	
Output 1: Volumes (ML/per year)	33 000	81 000	90 000	86 000	45 000	4 000	1 636 000	114 000	440 000	2 529 000
Input radial movement	-	-	-	-	-	-	-	-	-	-
Input slack movement	-	-	-	-	-	-	-	-	-	-
Input target	33 000	81 000	90 000	86 000	45 000	4 000	1 636 000	114 000	440 000	2 529 000
DMU peers	9;5;6	6;9;5	5;6;9	6;9;5	5	6	7	9;5;6	9	
Model 3: VRS										
Input 1: Total expenditure (R'000)	460 000	765 000	690 000	574 000	550 000	50 000	11 429 000	1 545 000	2 162 000	18 225 000
Input radial movement	-	-	-	-	-	-	-	-	-	-
Input slack movement	-	-	-	-	-	-	-	-	-	-
Input target	460 000	765 000	690 000	574 000	550 000	50 000	11 429 000	1 545 000	2 162 000	18 225 000
Output 1: Volumes (ML/per year)	33 000	80 000	92 000	91 000	44 000	3 000	1 625 000	120 000	453 000	2 541 000
Input radial movement	-	23 639	31 747	11 143	46 985	-	-	24 779	-	138 293
Input slack movement	-	-	-	-	-	-	-	-	-	-
Input target	33 000	103 639	123 747	102 143	90 985	3 000	1 625 000	144 779	453 000	2 679 293
Output 2: Bulk Water Tariffs (R/kl)	11	8	6	7	4	7	9	9	7	
Input radial movement	-	2	2	1	4	-	-	2	-	
Input slack movement	-	-	-	-	-	-	-	-	-	
Input target	11	10	8	8	8	7	9	11	7	
DMU peers	1	7;9;1	6;1;9	1;9;6	6;1;9	6	7	1;7	9	
Model 4: VRS										
Input 1: Total expenditure (R'000)	460 000	765 000	690 000	574 000	550 000	50 000		1 545 000		4 634 000
Input radial movement	-	-	-	-	-	-		-		-
Input slack movement	-	-	-	-	-	-		-		-
Input target	460 000	765 000	690 000	574 000	550 000	50 000		1 545 000		4 634 000
Output 1: Volumes (ML/per year)	33 000	80 000	92 000	91 000	44 000	3 000		120 000		463 000
Input radial movement	-	3 779	2 464	-	38 231	-		-		44 474
Input slack movement	-	-	-	-	-	-		-		-
Input target	33 000	83 779	94 464	91 000	82 231	3 000		120 000		507 474
Output 2: Bulk Water Tariffs (R/kl)	11	8	6	7	4	7		9		
Input radial movement	-	0	1	-	3	-		-		
Input slack movement	-	-	-	-	-	-		-		
Input target	11	8	7	7	7	7		9		
DMU peers	1	4;7;1	4;7	4	1;6;4	6		8		

Sources: Author’s calculations based on efficiency results.