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Water systems modeling and optimization

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Abstract

Water utilities provide an essential service of delivery of clean and safe drinking water to society. As migrations to cities increase, the demands on water utilities are increasing. Traditionally optimisation was focused on the reduction of energy demand and water losses of the water distribution network (WDN), but contemporary networks are integrated, and optimisation is not limited to the WDN. In the current landscape, business sustainability is paramount. Sustainability is inclusive of the economic, environmental and social performance of the business. This study develops an approach to determine the sustainability performance of a water utility, defined as the Business Performance Index (BPI). The BPI is a function of a water utilities key performance indicators of energy demand, water volume entering the WDN, cost and execution time. The approach (1) quantifies the BPI based on current operational practice, (2) allows the business to set a target BPI and (3) identifies the business operational parameters to achieve the target BPI. The approach is demonstrated by application to a metropolitan water utility, where target BPIs for time t_1 and t_2 are set at 5% and 8% lower than the quantified baseline BPI. The approach determines that the target BPIs are not always achievable given business constraints and interdependencies, hence a realisable BPI is defined. The realisable BPI at time t_1 and t_2 is 2.3% and 6.4% less than the baseline, respectively. For each of the realisable BPIs the required statuses of the operational variables are defined. The results further identify three key operational aspects for improvement, invoicing, business process energy demand and process energy demand. The approach and the defined BPI enables a water utility to optimise energy demand, water losses, cost and execution time, holistically, as the interdependencies are considered.

Keywords: Discrete Event Modelling (DEM); Systems Dynamics Modelling (SDM); Systems Dynamics (SD); Optimisation; Energy generation

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1. Introduction

Access to safe and clean drinking water is a basic human right, supported by the United Nation's sustainable development Goal 6 [1]. Only 0.01% of potable water is available from the available 3% on earth [2]. More than 2 billion lack access to safe drinking water and basic sanitation [3] and nearly 4 billion people could be living in water-scarce regions by 2050 [4]. South Africa (SA) is a semi-arid country with constrained water supplies. SA has an average rainfall of 450 mm/year, significantly lower than the world's average of 860 mm/year [5]. The supply of water to households, buildings and industry is via water distribution networks (WDNs), which are owned, maintained and operated by cities, water boards or private water companies. In SA, the water losses in a WDN varies between 30 to 40%, and can increase to 58% in rural areas [6]. In 2018, Cape Town, the capital city of SA, experienced a severe water crisis, with the risk of the taps running dry. This emphasised the need for sustainable practices in the South African water sector.

The entities owning, operating and maintaining WDNs, will henceforth be referred to as water utilities. Water utilities, whilst providing an essential service is still a business, and is required to be self-sustaining. Water utilities experience significant challenges; water losses and its associated revenue losses, high energy demands, environmental impact of business operations, increasing demand, and aging infrastructure. In the current global business landscape, business sustainability is vital and dependent on the financial, environmental, and social performance. Defining the business sustainability, requires delineation of the business financial, environmental and social performance.

The Fourth Industrial Revolution (4IR) presents opportunities for sustainable operations and economic growth for the water sector, termed "Digital Water," or "Water 4.0". 4IR drives sustainability via adoption of technologies, to create a fully integrated digital business. There are various technologies available, ranging from industrial internet of things (IoT), virtual reality (VR), augmented reality (AR), big data analytics (BDA), artificial intelligence (AI) and 3D printing. The identification of the appropriate technology for application is crucial, as it impacts the business financial, environment and social performance. Thus, the definition of the current business sustainability is necessary. This study develops a digital model of a water utility, inclusive of all activities (humans resources to operations, to finances to maintenance), to quantify the business sustainability, defined as the Business Performance Index (BPI). The water utility model has the capacity to determine the impact of changes on the BPI.

2. Literature Review

Water utilities provide an essential service of distributing safe drinking water to society. The water utilities distribute potable water via WDNs. These WDNs can span hundreds of kilometres and comprise piping networks, pumps, compressors, and control and instrumentation. However, these WDNs are a significant source of water loss. The water loss in developing countries is 45 million cubic meters per day, with an associated economic value of 3 billion US dollars annually [7]. The global non-revenue water loss is estimated at 346 million cubic meters per day, equivalent to 39 billion US dollar annually [8]. Reducing the water loss by one third, can provide 800 million people with water, based on a consumption of 150 litres per day [8]. This is especially significant given that urban populations, are expected to increase from 55% in 2018 to 68% by 2050 [9]. Reducing water losses has multiple benefits for a water distribution utility; increase in water quality, reduction in energy demand, water supply reliability, and financial savings [8]. Water loss management is priority for water utilities and governments, towards development of sustainable businesses and societies, respectively.

The water industry was accountable for 4% of global electricity consumption in 2014 [10]. The specific energy consumption of WDNs of developing countries is less than 0.30 kWh/m^3, while that of developed countries typically range between 0.4 – 0.79 kWh/m^3, with Germany having a specific energy consumption of 1.71 kWh/m^3 [11]. Water pumps are the primary consumer of electricity, and can be as high as 90% of electricity consumption [10]. Increasing operational costs limits the utilities capacity to expand infrastructure and services, adoption of technologies to improve performance and maintenance of infrastructure. Increasing operational costs are ultimately transferred to the customer, impeding access to water. Reference [11] analysed the factors influencing the specific energy consumption of WDNs in China and determined that the specific energy consumption of water distribution networks decrease as the volume of water supplied increases and increases with a rise in pipeline network pressure.

The “smart water” revolution is expected to capacitate the water industry to integrate and manage both the vertical and horizontal value chains, i.e., the technologies aspect, business stack system, water supply/demand activities, water infrastructure/network and business strategy/management. 4IR advances the integration of information technology (IT) and operational technology (OT), and inbound supply chain to distribution to provide for the holistic integration of water as a business. Horizontal integration is the integration of different IT systems across various water infrastructure networks and business process planning which requires exchange of information, energy and resources. These different systems include customer relationship management, supply chain management, vendor management, operations management, asset management, human resource and capacity management and financial management. Vertical integration is the integration of different IT systems at varying hierarchical levels within the organization. This includes sensors, operational network, manufacturing data, enterprise resource planning, business intelligence, and big data and analytics. Vertical integration implementation provides a complete, single view of entire processes and allows a central dashboard that is applicable for monitoring and controlling of every aspect of water demand and supply across the different water networks [12, 13].

WDNs are complex, comprising of various sub-systems, including pressure management, maintenance management, quality, leak detection and operational optimisation. These sub systems are integral for a WDN and should deliver in unison. The integration of a WDN is highly dependent on data collection via sensors. The sensor integration presented by [14] provides for sensor integration that can deliver to all sub systems; data integration towards a digital WDN. Reference [15] adopted advance control systems in the form of self-tuning loops to conduct pressure management in WDNs. Reference [16] developed a comprehensive online model for WDNs with integration into the SCADA network for real time data. The model predicts water utilisation and hydraulics in the network. Refence [17] conducted a case study on the application of real time control at the Benevento city WDN. The application of real time control resulted in reduced pressure variability within the WDN, and a 1L/s decrease in minimum night flow, inferring leakage reduction [17]. Reference [18] discussed a drinking water system that integrated SCADA, telemetry, and automatic meter reading with databases, water management modules and a geographic information system (GIS) system in real time. This provided the utility with real time demand data, operational data, and irregularities in operations, enabling optimisation in real time [18].

Reference [19] developed a multi-criteria assessment tool for evaluating the performance of water supply system providers with interval-valued intuitionistic fuzzy number and pair-wise comparison. Five criteria were selected; technical, socio-cultural, environmental, economic and governance, which were applied in demonstrating the developed tool. Reference [20] presented a digitally integrated platform for water resources in a province in China. The cloud-based platform served as a real time data sharing platform, from sensor to enterprise for the entire province. This recent study is positive and illustrates a digital WDN is a reality.

Literature defines the complexity, energy usage, water losses and other critical aspects of the WDN. The key focus is managing or reducing water losses. There is limited focus on the business as a whole; optimisation of the operations of the business (inclusive of supporting functions of HR, safety, health and environment, finance) to reduce water losses, and optimise energy and resource utilisation. The ability to predict optimisation opportunities to reduce water losses, energy utilisation and cost is the focus of this study. This study proposes a multi-pronged approach in defining and optimising a water utilities BPI.

3. Methodology

A business process (BP) details the logical steps in completion of a business task, from the initiation of the task to the end. A business process model (BPM) provides a graphical illustration of a business process. Water utilities are operated and managed by execution of BPMs. The business task can vary from leak management to establishment of a business mission. BPs are hierarchically categorized, beginning at Level 0, and proceeding to a Level *n*. Level 0 is typically at a business function level such as human resources (HR), finance, information, and communication technology (ICT), while Level “n” is the activity level specifying actions for execution of a specific business task.

Business process simulation (BPS) evaluate the performance of a process under multiple scenarios, allowing comparative analysis of options towards improving the performance of a business process [21]. The n^{th} level processes are comprehensive and specific to the task being executed. The simulation of the n^{th} level process enables quantification of the; resources required (laptops, printers, switches, firewalls, pumps, compressors, HVAC), utilisation time and energy demand of the resources and skills and time requirement of the personnel. For the purposes of this study, a four-level hierarchy is adopted for the water utility.

- Level 0 - business functions, such as operations, maintenance, finance.
- Level 1 - process areas per business function, such pressure management within the operations function.
- Level 2 - business processes per process area, such as pressure reduction within the pressure management process area.
- Level - specific steps within each BP, such as open valve x at location y for the pressure reduction BP.

The expansion of the processes from Level 0 to level 3 is illustrated in Equations 1 to 4.

$$Level\ 0 = \sum_1^m Business\ functions \tag{1}$$

$$Level\ 1 = \sum_1^l \sum_1^m Process\ areas \tag{2}$$

$$Level\ 2 = \sum_1^m \sum_1^l \sum_1^k Business\ processes \tag{3}$$

$$Level\ 3 = \sum_1^m \sum_1^l \sum_1^k \sum_1^j Business\ process\ steps \tag{4}$$

For Equations 1 to 4, *m* is the number of business functions, *l* is the number of process areas, *k* is the number of business processes and *j* is the number of business process steps. In the operation of a water utility business tasks do not occur in silo, the tasks are integrated with other tasks. For example, maintenance activities are linked to, (1) finance tasks for purchasing of required materials to execute the maintenance task, (2) customer service management to inform customers of disruptions to water supply, if applicable. At Level 3 , all business activities integration are considered. Thus, the simulation of Level 3 processes, as defined by Equation 4, creates a comprehensive digital representation of the water utility. henceforth referred to as the water utility model. BPMs are developed in Microsoft Visio for all activities conducted by the water utility. The BPMs are exported from Microsoft Visio to Microsoft Excel, which enables development of the water utility simulation model in Microsoft Excel VBA. In the operation of a water utility there are fluctuations in operations, as each variable has its own operating range. Example of variables include; number of water leakages, number of maintenance requests, number of in-arrears customers, number of customer queries and complaints and number of pressure deviations across the WDN. This creates an inherent level of uncertainty in the business. To simulate the uncertainty the Monte Carlo Simulation approach is adopted, with randomness applied to the variables, constrained to minimum and maximum range of the specific variable. The Monte Carlo Simulation is executed via an algorithm within the water utility model, until the change in the standard error of the mean of the target output is negligible.

The execution of the water utility model, in Microsoft Excel VBA, quantifies the business energy demand, carbon dioxide (CO_2) emissions, water volume entering the WDN, execution time of tasks, personnel hours, and energy and personnel costs. Since business activities may occur daily, weekly, bi-weekly, monthly, quarterly or annually. all activities are simulated to a common basis of per annum.

The water utility model, based on business process simulation, is the building block for defining the Business Performance Index (BPI). The BPI is a function of the key performance indicators (KPIs) of a water utility; energy demand, water volume entering the WDN, cost and execution time . The volume of water entering the WDN is critical as it is an indication of the water loss in the WDN; the higher the water loss the higher the entering volume. The higher the water loss, the higher the financial losses due to non-revenue water and higher operating costs. Execution time refers to the time taken to execute the various business tasks. The key variables influencing each KPI are detailed in Equations 5 to 8.

$$Energy\ Demand = f\{resource\ type(HVAC, ICT, process, network); execution\ time\} \tag{5}$$

$$Exceution\ Time = f\{personnel\ skills; resource\ type; activity/task\} \tag{6}$$

$$Cost = f\{energy\ demand, execution\ time, personnel\ time\} \quad (7)$$

$$Water\ Volume = \{Operational\ practice;\ maintenance; water\ loss\} \quad (8)$$

The four KPIs, each with its own set of influencing variables (with some common variables), necessitates a multi-objective optimisation (MOO) approach to develop a singular objective function representative of the BPI. The scalarisation technique of equivalent weighting of each function is adopted in defining the BPI objective function [22, 23]. An equal weighting approach for each KPI is used, due to the lack of quantifiable data for ranking of the four KPI's

$$BPI = w_1 f_{ED} + w_2 f_{ET} + w_3 f_C + w_4 f_{WV} \quad \text{Constrained to } \textstyle\sum_1^4 w = 1 \quad (9)$$

In Equation 9 w is the weighting of each function, f_{ED} is energy demand, f_{ET} is execution time, f_C is cost and f_{WV} is water volume. To solve Equation 9, objective functions are required for each of the KPIs. To develop the objective functions the water utility model is executed.

The execution of the water utility model, inclusive of the Monte Carlo Simulation, creates a data set. The data set comprises the variables and KPIs. For each data point (each run of the Monte Carlo simulation) the variables statuses and the associated energy demand, execution time, cost and water volumes are defined. Linear regression is applied to the dataset to, firstly identify the variables impacting each of the four KPIs, and secondly to develop predictive functions for each KPI (based on the significant variables). The dataset is divided into the learning and validating sets. The learning dataset comprises 70% of the original data and is applied in developing the predictive functions, while the remaining 30% is applied in validating the predictive functions. The linear predictive functions developed for each of the KPIs is in the following format, with the energy function used as an example:

$$f_{eED} = C + C_{E1}x_{E1} + C_{E2}x_{E2} + C_{E3}x_{E3} + C_{E4}x_{E4} + C_{E5}x_{E5} \ldots\ldots + C_{En}x_{En} \quad (10)$$

In Equation 10 C is a constant, is variable influencing energy demand, C_E is coefficient of the respective variable and n is number of variables. Similar equations are developed for the remaining KPIs, with the key differentiator being the variables applicable to each KPI. A sensitivity analysis is conducted on each of the four predictive functions to eliminate the insignificant variables. The dataset also identifies the minimum and maximum value of each objective function. The definition of the predictive function for each of the KPIs, enables resolution of the BPI.

In solving equation 9, a water utilities current BPI is determined. The next step is optimisation of the BPI. The water utility defines a target BPI, a value less than the current BPI, as the objective is to reduce energy demand, costs, water volume entering the WDN, and execution time. With the target BPI set, equation 9 is now solved in reverse by applying the solver function. This approach identifies the new states of the four KPIs constrained to the maximum and minimum value of each function, to achieve the targeted BPI. The solver function is then applied to each KPI function to determine the new statuses of the significant variables. These variable statuses are then updated on the BPM for operational execution. The methodology detailed above is illustrated in Figure 1.

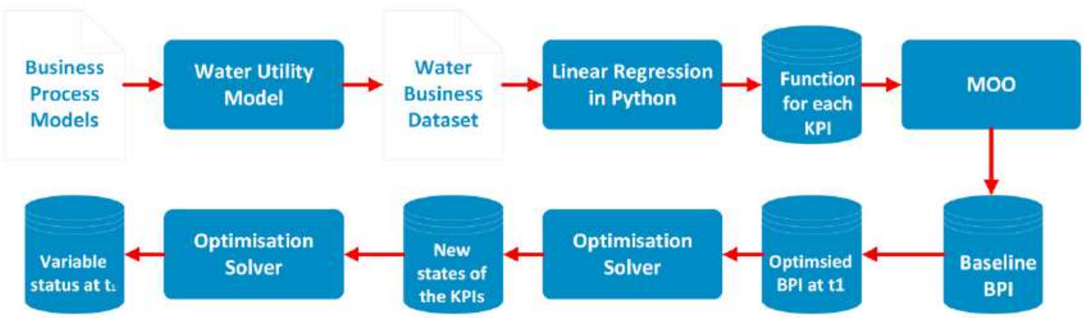


Fig. 1. Approach to defining and optimising BPI

The proposed model achieves three needs of a water utility, (1) quantifies the BPI based on current operational practice, (2) allows the business to set a target BPI and (3) identifies the business operational parameters to achieve the set target.

4. Results

A metropolitan water utility BPI is evaluated, as per the methodology illustrated in Figure 1. The BPs for the water utility were developed utilising the APQC Cross Industry Process Classification Framework and validated with experts in water utilities operation and management. The business processes are converted to business process models and the water utility simulation model is developed inclusive of all business activities and associated integration. All required process data is extracted from publicly available sources such as energy databases and annual reports. In analysis of the developed business processes, 77 business variables are identified ranging from water flow rate, number of maintenance requests, number of new personnel recruitments, to number of purchase orders issued. In execution of the Monte Carlo Simulation, the 77 variables are randomised, limited to the maximum and minimum range of each variable, until the change in the standard error of the mean of the energy demand is negligible. For the water utility, this is realised at 2800 runs.

This creates an 81 by 2800 data matrix, with 81 representing the 77 identified business variables and the four KPIs of energy demand, execution time, water volume and cost. For each of the 2800 runs, the 77 variables and the four KPIs have a specific variable status and output, respectively. The data matrix is analysed via linear regression in Python and predictive functions are developed for each of the KPIs. A sensitivity analysis is conducted on each of the four functions to eliminate insignificant variables. The final functions for each of the four KPIs are detailed below.

Execution Time Function: Calculates the business execution hours, per annum

$$f_{ET} = -9.16 * 10^{-5} - 1.217A - 1.682B + 0.0085C + 0.134F + 0.267G \tag{11}$$

Energy Demand Function: Calculates the business energy demand per annum

$$f_{ED} = 0.0016 + 0.739B + 0.0005C + 2.109G - 0.064H + 0.064M + 0.002J \tag{12}$$

Water Volume Function: Calculates the volume of water entering the WDN per day to meet final demand

$$f_{WV} = -1.42 * 10^{-6} - 1.32 * 10^{-7}D + 2.53 * 10^{-7}E + 11.05I \tag{13}$$

Cost Function: Calculates the operational costs per annum

$$f_C = -0.0027 + 1.002C + 0.014I + 0.952G + 1.582K + 0.119M \tag{14}$$

To avoid distortion of Equation 9,due to the magnitudes of the KPI outputs, the water volume entering the WDN is set at per day, with the remaining KPIS set at per annum. Each variable of Equations 11 to 14 is detailed in Table 1, together with the allowable operational range. Due to the varying magnitudes of the energy demand, it is classified as (1) ancillary energy demand - all business activities (HR, finance, customer services management, SHEQ) energy demand excluding the WDN operational demand, (2) HVAC energy demand - facilities energy demand and (3) process energy demand - WDN operational energy demand inclusive of pumps, compressors and control and instrumentation. BPMs have decision blocks, which determine the path followed in execution of a business task. This impacts the resources utilised, personnel requirements, execution time, and costs. The variables D and E represent decision blocks with two possible options; hence the range is 0 to 1. For variable D, path A is followed if the water balance is correct, with, path B followed if the water balance is incorrect. Path B is a more intensive process path requiring additional resources, time, and personnel as the reason for the water balance not reconciling must be resolved.

Table 1. Variable influencing the four functions of the BPI

Variable	Factor	Min Value	Max Value
Ancillary energy demand per annum (kWh)	A	750 266	963 051
Ancillary energy cost per annum (ZAR)	B	997 854	1 280 858
Personnel costs per annum (ZAR)	C	914 045 366	1 122 085 586
Is the water balance correct (0 = No and 1 = yes)	D	0	1
Is the pressure deviation due to a fault at the bulk water supplier (0 = No and 1 = yes)	E	0	1
Number customer invoice queries per month	F	229	2 498 500
HVAC energy demand per annum (kWh)	G	2 006 186	2 006 186
Personnel hours per annum (hr)	H	5 726 025	7 125 083
Process energy demand per annum (kWh)	I	101 382 400	144 832 000
Process energy cost per annum (ZAR)	J	134 838 592	192 626 560
HVAC energy cost per annum (ZAR)	K	2 668 227	2 668 227
Water flowrate per day (l/day)	L	1 120 000 000	1 600 000 000
Network energy demand per annum (kWh)	M	2 481 033	2 481 033

As per the equivalent weighted multi-objective function, the BPI is defined as:

$$BPI = 0.25f_{ET} + 0.25f_{ED} + 0.25f_{WV} + 0.25f_{C} \quad (15)$$

Using the current operational conditions, the baseline BPI is calculated, with the results in detailed in Table 2.

Table 2. Baseline BPI and KPI outputs

BPI	Energy (kWh)	Water (ML/day)	Cost (ZAR)	Execution Time (hr)
734 014 938	5 848 053	1 600 000 000	1 323 131 939	7 079 760

The baseline status of each of the significant variables is detailed Table 3.

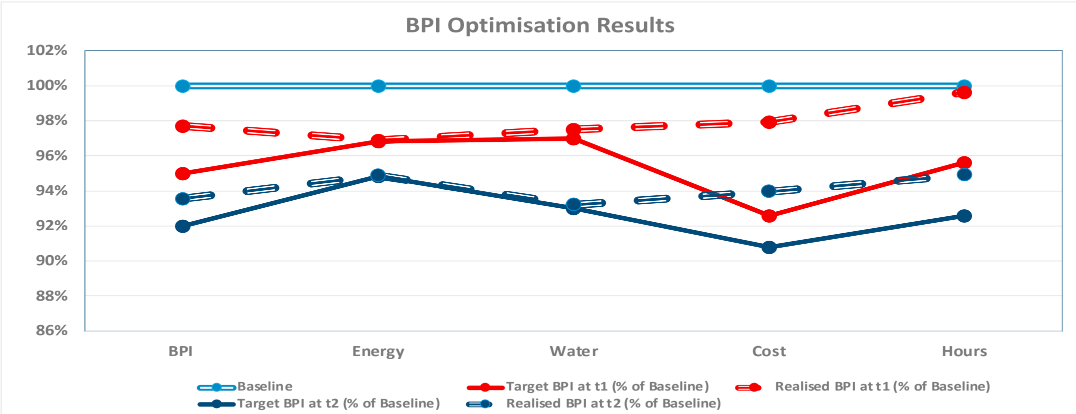
Table 3. Baseline operational status of the variables

Variable	Factor	Operational status
Ancillary energy demand per annum (kWh)	A	963 051
Ancillary energy cost per annum (ZAR)	B	1 280 858
Personnel costs per annum (ZAR)	C	1 122 000 000
Is the water balance correct (0 = No and 1 = yes)	D	1
Is the pressure deviation due to a fault at the bulk water supplier (0 = No and 1 = yes)	E	1
Number customer invoice queries per month	F	2 498 500
HVAC energy demand per annum (kWh)	G	2 006 186
Personnel hours per annum (hr)	H	7 000 000
Process energy demand per annum (kWh)	I	144 832 000
Process energy cost per annum (ZAR)	J	190 000 000
HVAC energy cost per annum (ZAR)	K	2 668 227
Water flowrate per day (*l*/day)	L	1 600 000 000

Network energy demand per annum (kWh)	M	2 481 033

In optimisation of the BPI, two reduced BPI's at time t_1 and t_2 are defined. Reduced BPI's (in reference to the baseline BPI) are the aim, as it is achieved by reductions in energy demand, water volume, costs and execution time. The reduction of the KPI's result in improved sustainability of the water utility. BPI at t_1 is set at 5% lower than the baseline, whilst at t_2 it is set at 8% lower. The targets are defined at times t_1 and t_2, as reducing the BPI would logically occur in a phased approach beginning with small increments and increasing steadily thereafter.

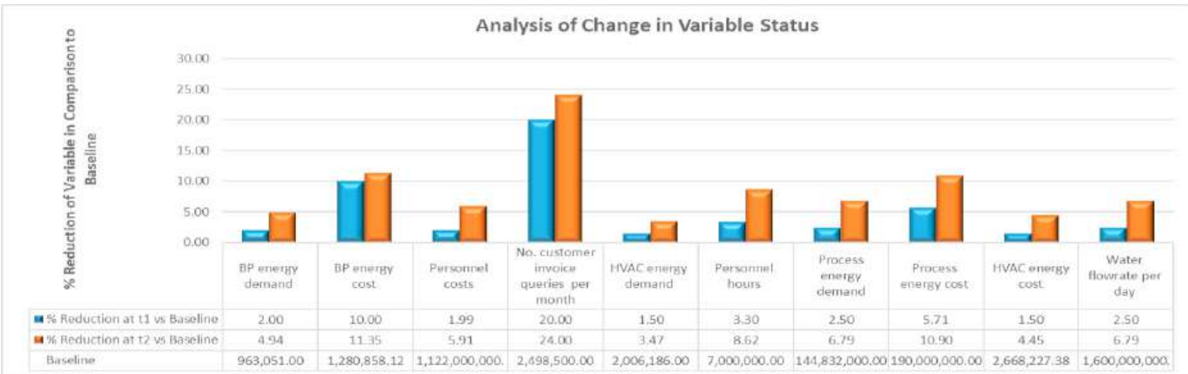
The results illustrated in Figure 2 demonstrate that achievement of set targets is not always possible given business constraints and interdependencies, hence a realisable BPI is defined. The realisable BPI is as close as possible to the target BPI. Figure 2 illustrates that the realisable BPIs at t_1 and t_2 are 2.3% and 6.4% lower than the baseline.



	BPI	Energy	Water	Cost	Hours
Baseline	100%	100%	100%	100%	100%
Target BPI at t1 (% of Baseline)	95%	97%	97%	93%	96%
Realised BPI at t1 (% of Baseline)	98%	97%	98%	98%	100%
Target BPI at t2 (% of Baseline)	92%	95%	93%	91%	93%
Realised BPI at t2 (% of Baseline)	94%	95%	93%	94%	95%

Fig. 2. Results of BPI optimisation

The objective functions of the KPI's are set at the respective realisable target values, and the corresponding states of the significant variables determined. The new states of the significant variables are presented as a percentage reduction from the baseline state, refer to Figure 3.



	BP energy demand	BP energy cost	Personnel costs	No. customer invoice queries per month	HVAC energy demand	Personnel hours	Process energy demand	Process energy cost	HVAC energy cost	Water flowrate per day
% Reduction at t1 vs Baseline	2.00	10.00	1.99	20.00	1.50	3.30	2.50	5.71	1.50	2.50
% Reduction at t2 vs Baseline	4.94	11.35	5.91	24.00	3.47	8.62	6.79	10.90	4.45	6.79
Baseline	963,051.00	1,280,858.12	1,122,000,000.	2,498,500.00	2,006,186.00	7,000,000.00	144,832,000.00	190,000,000.00	2,668,227.38	1,600,000,000.

Fig. 3. Status of variables to achieve the realisable BPI at t_1 and t_2

The variables with highest capacity for optimisation are the number of customer invoice queries per month, BP energy cost and process energy cost. The customer invoicing process can be improved by automation and the use of smart water meters for collection of accurate customer consumption data. The BP energy cost is directly linked to the BP energy demand. Repetitive and high-volume tasks such as customer invoicing, customer queries handling, purchase order generation, and payments can be automated. Automation would significantly reduce the time taken to execute these tasks, thereby reducing the BP energy demand and associated costs. Automation of these tasks would also facilitate data gathering, with the data analysed to provide insights on process improvements. Similarly, process energy cost is directly linked to process energy demand. Pumps are the highest consumers of energy in the WDN. Variable speed drives (VSD) can significantly reduce the energy demand of pumps, as it varies the speed of the pump motor with a change in the water flow. 4IR technologies of IoT, Industrial Internet of Things, and BDA have significant potential for the water industry. The adoption of IoT enables integration of the various components of the WDN and ERP systems. With an integrated set of systems comes a continuous and consistent stream of real time data, which collated over time is ideal for BDA for optimisation.

The water flowrate is directly proportionally to the process energy demand; a 2.5% decrease in water flowrate results in corresponding 2.5% decrease in process energy demand for the BPI at time t_1, with a similar pattern for BPI at t_2. Reducing the water losses across the WDN, has a domino effect of decreasing the volume of water to be pumped per day, process energy demand, and process energy costs. 4IR based leak detection systems have been adopted globally and can assist in timeous leak identification, driving reductions in water losses. HVAC has the lowest potential for improvement, as HVAC infrastructure improvements are cost and time intensive, requiring step wise improvements across a period. The results demonstrate the capacity of the model to identify and optimise the BPI, including the status of the variables for the optimised state. It also provides insights into areas for improvement.

5. Conclusion

As the demand for water increases, and available water resources become increasingly constrained, water utilities are under severe pressure to optimise business performance. A core component of the water utilities is the WDN. The traditional approach to optimisation focuses on reduction of the WDN energy utilisation and water loss, but this is limited in the current business landscape. The proposed approach is holistic, considering the economic, environmental, and social aspects. In this study a sustainability business measure, defined as the BPI is developed for water utilities. The BPI is a function of the KPIs of energy demand, water volume entering the WDN, cost and execution time.

In definition of the BPI the following were developed and executed; a comprehensive water utilities model based on BPs; Monte Carlo Simulation, linear regression and MOO. The BPI approach was demonstrated by application to a metropolitan water utility. The baseline BPI was determined based on current operational practice, with the target BPIs at times t_1 and t_2 set at 5% and 8% lower than the baseline respectively. The proposed approach illustrated that the target BPIs are not always achievable given business constraints and interdependencies, thus a realisable BPI is defined. The realisable BPIs at t_1 and t_2 is 2.3% and 6.4% lower than baseline, respectively. The statuses of the significant variables for attainment of the realisable BPIs were determined. The key variables identified for improvement are number of customer invoice queries, business process energy demand and process energy demand.

Future work is to refine the equal weighting applied in determining the BPI, as it is unlikely that the KPIs are equally weighted. This would require significant additional data. The deployment of a fully integrated network is also currently in progress, which would lead to significant refinement and improvements to this study. The value-add of the proposed approach is its applicability to any water utility, with only the BPs and resources requiring updating.

Acknowledgements

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