Modelling Waste Incineration and Wind Energy for Water Desalination

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EXTENDED ABSTRACT

Water shortage issues have been growing concerns in many cities around world in recent years, especially in eastern cities of Australia. This paper explores use of waste incineration energy complemented by alternative energy for seawater desalination for a drought stricken city in Eastern Australia. Our research is motivated by the recent successive severe drought conditions that hit many Australian cities, compounded with an additional strain from the fast growing population. While we dump our waste into the Australian landscape, in more densely populated cities including Vienna, Austria, and a large number of cities in Japan, the waste is incinerated to obtain thermal energy for various purposes including heating and electricity generation. The waste is used as a cheap fuel source while reducing the amount of space needed for landfill. The seawater desalination has been successfully practiced for quite sometime particularly in Middle Eastern counties. To deal with increasing water shortage crisis, more cities around the world have opted or are considering the seawater desalination to complement their water demand. At this time, to the best of our knowledge, the combination of both - waste incineration and seawater desalination - has not been studied or implemented. Motivated by this promising combination, we started investigating the potential of seawater desalination powered by waste incineration using the Gold Coast City, Australia as a case study. If we can incinerate the waste to power a desalination process, we reduce water shortage, and at the same time reducing an amount of landfill. The seawater desalination is an expensive production process, but it ensures continuation of fresh water supply in dry weather conditions.

Our model follows a dynamic systems approach with control theory as basic discipline. This approach allows the observation of long-term behaviour of a system and its dynamics, with its effects more visible at a high level of resolution than with statistical modelling. The model is implemented with modular hierarchical structure in Matlab/Simulink. This allows gradual building of the complexity into the model. We have overcome a number of modelling difficulties including lack of accurate dam catchment data by incorporating other modelling techniques such as artificial neural networks. We then incorporated the mathematical model retrieved from the artificial neural networks into our model. The model presented in this paper is an extension and refinement of our earlier model with integrated specific sub-models derived from artificial neural networks.

The focus of this work is on simulating the possible amount of energy and the desalinated water that can be generated by clean city waste incineration. We do this while simulating the increasing population, and their water demand. We then calculate the additional amount of alternative energy that would be required to complement the waste incineration energy for producing sufficient supply of desalinated water.

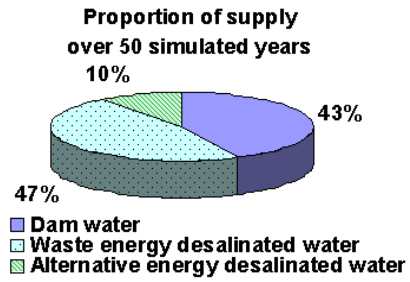

Figure 1. Proportion of simulated water demand fulfilled by each supply

In this paper we present the calibration of the model, followed by a long-term experimental simulation, while incorporating population growth, with its growing fresh water demand and waste generation. The result indicates that seawater desalination by incinerating the waste itself alone is able to supply over 40% of water demand continuously throughout 50 simulated years as shown in Figure 1.

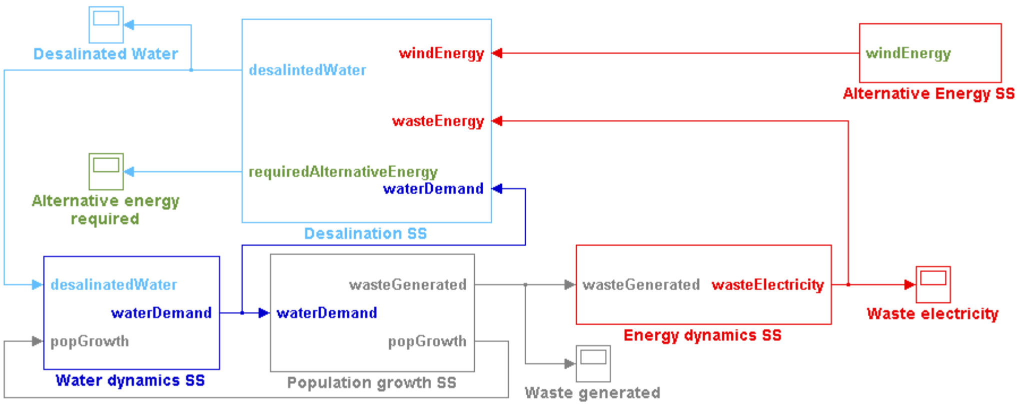

Figure 2. Top level of the comprehensive model

Acronyms

ANN	Artificial Neural Networks
EP	Epoch
GCCC	Gold Coast City Council
HLN	Hidden Layer Neuron
MSE	Mean Square Error
RO	Reverse Osmosis
TEG	Training Error Goal (MSE)
WC	Water Consumption
WS	Window Size

1. INTRODUCTION

This paper presents the modelling of seawater desalination powered by waste incineration with the purpose to complement fresh water supply in a drought-affected area. Our research is motivated by the increasing water shortage caused by successive severe drought conditions that hit many Australian cities compounded with an additional strain from the fast growing Gold Coast population. This is in addition to the successful use of waste incineration to generate energy in Europe and Asia as well as the seawater desalination in dry countries such as Saudi Arabia where the seawater desalination is used for 70% of drinking water supply (SAIR 2005). In Gold Coast, we currently dump 87% of our non-recyclable waste into landfills, despite the fact that almost 70% of the waste is combustible (GCCC 2005). If we can incinerate the waste for energy to desalinate the seawater, we reduce the water shortage, while at the same time reducing an amount of landfill. The use of waste as possible fuel source with additional alternative energy such as wind, aids to compensate some of the energy cost needed for seawater desalination operation.

The Gold Coast city has somewhat recovered from the worst drought between 2001 and 2003 thanks to one substantial rainfall in 2005, but the drought problem has been spreading in a wider area around Australia. In the long term, the predicted water demand of 465 million litres a day with projected population growth of up to 1.2 million by the year 2056, also causes an additional concern to city's infrastructure (ABS 2005, GCCC 2005). So far the city's solutions are transferring water from neighbouring Brisbane city through the pipeline and rise of the dam wall. However this pipeline option might not be risk free as the source of water, Wivenhoe dam, is also facing water shortage. Currently its dam level is less than 37% and the sizeable rainfall is not expected in the near future (SEQWater 2005, LCC 2005).

Our model follows a dynamic systems approach with control theory as basic discipline. This is to observe long term behaviour of the system while maintaining a high level of resolution without being side tracked by minutes details incorporated implicitly into the model. Another benefit of this approach is that dynamics of effect are more visible than in statistical modelling. The model shown in Figure 2 is an advanced model that is a refined and expanded version of our earlier model (Udono and Sitte 2004). This refined model developed in Matlab/Simulink® (Mathworks 2005) was expanded with specific sub-models derived by using other modelling techniques such as Artificial Neural Network (ANN) to overcome several modelling difficulties that arose due to lack of accurate data of the city such as dam catchments (Udono and Sitte 2005). Our model is designed such that it can be adapted to other cities by simply changing the local parameters.

2. COMPREHENSIVE MODEL

Our comprehensive model shown in Figure 2 can be divided into 3 major sections, water dynamics, energy dynamics, and population. Details of each section and its sub-modules are described below.

2.1. Water Dynamics Cycle

In our model, the water dynamics cycle consists of two major modules, desalination and dam level dynamics. The desalination module computes the amount of desalinated water that can be produced using available energy. The desalination method considered in our model is a Reverse Osmosis (RO) technique. RO is currently the most energy efficient desalination method and more desalination plants are built using this method. This requires energy, which in our case is the waste energy converted into electricity. The details of this are explained further below.

The dam level dynamics module has two core components, dam level change and water demand. Both of these components are based on ANN architecture retrieved from ANN experiments. Two major difficulties of constructing the dam level dynamic model are (a) the absence of data and information including unknown extent of the catchment area and (b) the disappearance of distinct rainfall pattern due to irregularities of the rain cycles and the vast difference in amount of rainfall. The unavailability of information about the catchment made lumped conceptual or physically based distributed model difficult to apply. ANN are mathematical constructs, which "learn" from a set of data samples and then classify and store patterns into classes. ANN have been successfully used in modelling specific aspects in hydrologic cycles. A number of researchers have successfully used ANN for forecasting river flow (Shamseldin 1997, Zealand et al. 1999, Gautam et al. 2000, Rajurkar et al. 2004, Lange. 1999). These researchers found an improvement in the predicting performance between 7% and 23 % with the ANN over other traditional rainfall-runoff models. The use of ANN was worthwhile move because the ANN can simulate without the amount and complexity of the data or any other effects occur in each hydrological cycle, but it is still able to simulate non-linearity of the dam level dynamics.

Modelling dam level dynamics with ANN

We collected the data including rainfall, ambient temperature and water consumption from the Gold Coast city water (GCCW 2005). We dealt with the time delay in the catchments water reaching the dam by using a window (set) of input data. We have used the data between the years 1999 and 2002 for training, and the data of 2003 for testing that is to simulate daily changes of dam level in percentage. The difficulty in preparing the output (change of dam level) was that to capture true dynamics of the dam only. This is the actual change of dam level caused by the climatic condition only. This required placing back the amount of previously consumed water back to the dam. We used a single hidden layer feedforward network with hyperbolic tangent sigmoid transfer function (tansig) for the hidden layer and a linear transfer function (purelin) for the output layer. The networks weights and biased were trained with gradient descent with momentum and adaptive learning rate. For this we used the Matlab functions traingdx and learngdx. We experimented a range of input variable combinations using rainfall, temperature, water consumption, and day of the year with a variety of epoch (EP: Iteration), training MSE goal (TEG) and hidden layer neuron (HLN). The selection of the most suitable ANN architecture was made by comparing the simulated dam level. The simulated dam level is calculated by converting the simulated change of dam level into the dam level using actual water consumption. The chosen ANN architecture was the input variable combination of rainfall and temperature using WS of 24 (HLN:4, TEG:0.00001, EP:50).

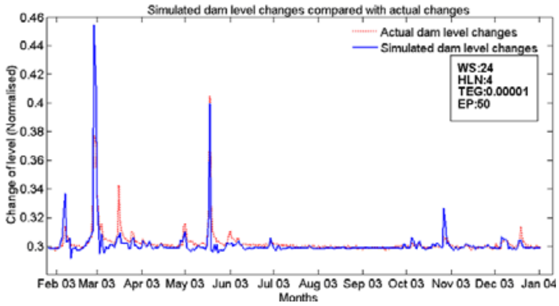

Figure 3. Comparison between simulated dam level changes and actual changes

The comparison of simulated dam level change and actual dam level change is shown in Figure 3. This had a MSE of 0.000043 against the actual 2003 dam level change. In Figure 3, a large error can result when dam level drops off suddenly just after a large raise of the dam level. This is because the training data contains irregularities such that at full dam level, and water leaving the dam through opened floodgates. We do not know which parts of the data are affected by this, neither can we quantity the amount of water that left the dam. As only limited datasets for non-El Niño years, the ANN has to be trained with this inconsistent pattern.

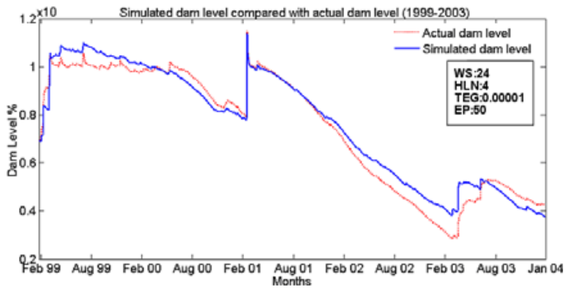

Figure 4. Simulated dam level compared with actual dam level

Figure 4 shows comparison between actual dam level and the simulated dam level using the simulated dam level changes with the chosen ANN and actual water consumption. It has MSE of 0.0024 and an average error percentage of 7.4%.

Modelling water demand with ANN

The water demand can be characterised as a variable that strongly depends on the population size, weather condition, and characteristic of the city. Numerous statistical models with multiple regression and time series have been developed for water demand modelling. Typically these models are developed by dividing the water use into a few categories such as base, seasonal and weather dependent water use etc. The multiple regression cascade model (Maidment and Parzen 1984) and daily water forecast transfer function model (Maidment et al. 1985) are some of the examples developed using statistical methods. Zhou et al. (2002) predicted daily water consumption of Melbourne, Australia by forecasting hourly water consumption from base use, daily, seasonal, and hourly demand according to climatic and seasonal data. However, these detailed models would not suit needs of our model. The problem of water demand simulation is comparable to the dam level dynamics as rainfall and temperature appear to be the most significant factors affecting the water demand. We believe that the daily water demand can be modelled with the ANN using data often used in the water demand model such as rainfall and temperature.

The same neural network configuration as the dam level dynamics modelling was used for these experiments. Again a number of input options combining rainfall, temperature, and day of the year with wide range of ANN parameters, epoch, training error goal and hidden layer neuron were experimented to find the most suitable ANN architecture for water demand. Trainings of ANN were carried out using dataset between Jan 1999 and April 2001 because of water restriction introduced in May 2002. The final comparisons were made after manually reducing the water demand by average reduction of same period from the date of a water restriction commencement. The chosen ANN architecture is input as a multivariate combination of rainfall, temperature, and day of the year using WS of 30 (HLN:4, TEG:0.002, EP:150). Figure 5 shows a comparison between simulated water demand from the selected ANN architecture and actual consumption between 1999 and 2003. It shows the close replication of the water consumption with good seasonal variation between summer and winter months with an average error percentage of 7.3%.

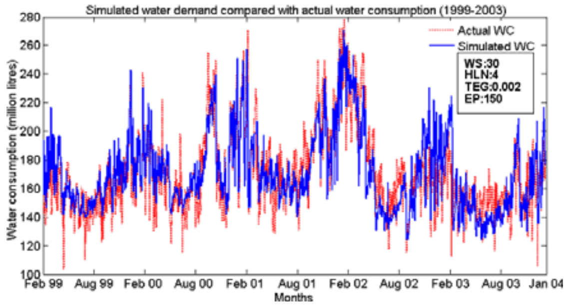

Figure 5. Comparison of simulated water demand and actual water consumption

2.2. Energy Dynamics Cycle

Waste energy estimation

For our water desalination model, we have to convert waste energy into electricity. The advantage of converting waste energy into electricity is that it can be linked to electricity grid and any remaining spare electricity could be used by other entities. We have collected numerous electricity consumption rates for RO from literatures. The collected consumption rates range between 2.04 kWh/m^3 and 9.38 kWh/m^3 (Busch and Mickols 2004, Avlonitis et al. 2003). We chose to use an average consumption of 5.18 kWh/m^3 from these collected data. A physical composition heating value estimation model by Ali Khan and Abu-Ghararah (1991) was chosen to estimate the heating value of the waste. The estimated heating value was found to be 9134.16 kJ/kg. The electricity generation from incinerating waste typically has a lower efficiency rate than the efficiency of fossil combustion, which typically has an efficiency of 30%-40%. We collected the waste incineration efficiency rates from various literatures. These rates ranged between 15% and 40% (Dajnak and Lockwood 2000, Morris 1996). We chose to use an average efficiency of 21.4%, which requires 16857 kJ for generating 1 kWh of electricity. The amount of waste generated by inhabitants of the city is estimated using data from the council report in 2002 (GCCC 2005), which is 1.1 tonnes per person per year.

Alternative energy estimation

We created an additional simulation module for the alternative energy to understand how much energy needs to be complemented for the water demand that cannot be fulfilled by the dam water and waste-energy desalinated water. In this study, we chose to calculate a how many 600 kW wind turbines are required using a typical capacity factor of 0.3 as an example of an alternative energy requirement. This module can be easily changed by plugging in any other type of alternative energy or just use it to calculate the necessary conventional fossil combustion energy.

2.3. Modelling Population Growth

The Gold Coast city is a narrow stretch along the coast with pronounced clusters of population density that cannot be simply averaged. To model its unique geographic characteristics and density distribution of Gold Coast, we decided to divide the city into four major sections, high-coastal, low-coastal, central and hinterland. We model them separately then combined together to obtain the total population of the city. High-coastal represents area that has already high density filled with high-rise buildings along the coastal area while low-coastal is coastal area that has a lower density due to less high-rise buildings, but expensive villas that are unlikely to be replaced by high-density dwellings in the next 20 or 30 years. In our population growth we also have taken into account the limitations to expansion due to the long shoreline and the already started merging with Brisbane on the northern parts. We applied logistic density dependent population growth model to each section using separate carrying capacity. This carrying capacity was determined based on the assumption that each section grows until it reaches the next higher up level of density. For example, the carrying capacity of low coastal is set to average density of the lower density area currently in the high coastal area.

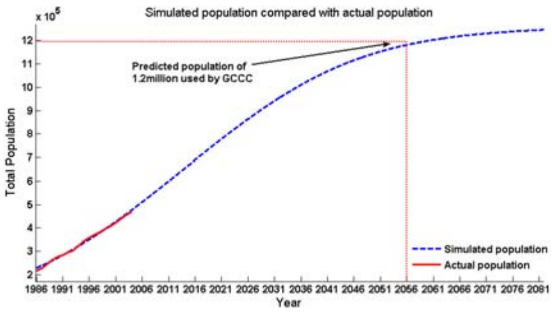

Figure 6. Simulated population of the city

Figure 6 shows the comparison of the simulated total population of the city and actual population of last 20 years. The result shows close simulation of the past population growth. This simulated population also closely matches the prediction used by GCCC of 1.2 million by year 2056 (GCCC 2005). The development of this growth model was necessary because there are only few population predictions at irregular intervals available.

3. INTEGRATION AND CALIBRATION OF DAM AND WATER DEMAND DYNAMICS

After selecting water demand and dam dynamics ANN architectures, these models and the population growth module were integrated together in the comprehensive model. The calibration focuses on finding an initial setting of the population, which determines the starting point (Date) of population growth effect on water demand. The calibrations were aimed at bringing the result as close as possible to the simulated dam level using the actual consumption between 1999 and 2003 shown in Figure 4.

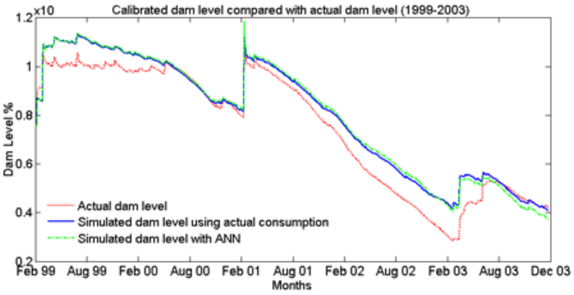

Figure 7. Calibrated dam level result

After several calibrations, we found that the population at the beginning of January 2001 was the best starting point. Figure 7 shows the final result of calibration. This final result has MSE of 0.00014 against simulated dam level with actual water consumption. Compared to the actual dam level, this calibrated result has MSE 0.0055. Although this is higher than the MSE of 0.0024 for the simulated dam level with actual water consumption (Figure 4), Figure 7 suggests that this difference is quite acceptable.

4. RESULTS AND DISCUSSION

After the calibration, we have carried out a long-term experimental simulation to study trend and major fluctuations. We focused on (a) amount of desalinated water that can be produced from waste incineration, (b) proportion of water demand that fulfilled by dam (rain) water and desalinated water, and (c) amount of alternative energy required to complement the disparity between available water and water demand. We study these while incorporating the population growth and irregular climatic conditions. We collected and analysed the El Niño record of the last 100 years. We then randomly distributed the dataset of 1999 and 2003 for our 50 years simulation scenario according to length and frequency of El Niño occurrences (Sitte 1998). We then applied data smoothing to each yearly data by using a running average of random periods between 1 and 7. Although the argument "if it happened in the past, it can happen again" is a valid one, we chose to do this because it is more moderate and realistic than attempting to randomly generating the climatic data sequence as it actually happened previously. The simulation is carried out based on an assumption that the water consumption or waste generation by an individual does not change throughout the simulation period. Because we neither know when (or if) nor how much of reduction or increase will occur. Validating such predictions is a complex issue. We start the simulation with the simulated population of 2006. The simulation results are compared using the yearly average results rather than a daily result for easier observation.

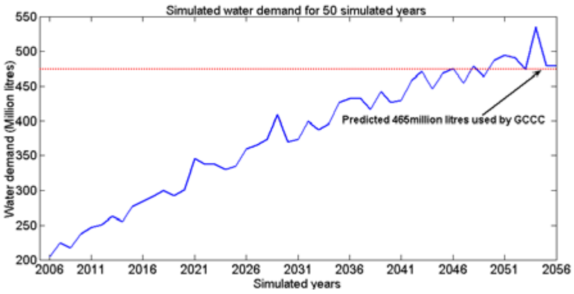

Figure 8. Simulated water demand

Figure 8 shows the simulated water demand for the simulated 50 years. It shows a clear change of water demand depending on the climatic conditions while the water demand is steadily increasing as the population grows. It reaches approximately 500 million litres a day towards the end of the simulation. This simulated water demand is found to be slightly over the water demand predicted of 465 million litres used by GCCC at year 2056.

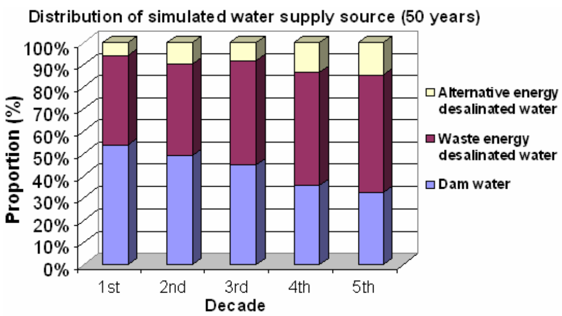

Figure 9. Distribution of simulated water demand

Figure 9 shows the proportion of water demand fulfilled by dam water, waste energy desalinated water, or alternative energy desalinated water. The comparison is made on ten year averages to avoid comparing abnormal values of water demand and rainfall caused by El Niño. In the first decade the dam water fulfils over 50% of water demand, which drops down to just over 30% by the 5th decade, as the amount of rainfall does not change throughout the simulation period. Meanwhile waste-energy desalination covers 40% of water demand in the first decade and increases to over 50% in the fifth decade due to increased waste-energy availability from the growing population. The needs for desalination by alternative energy started off with only 6% of water demand in the first decade. Although some of the increased water demand is fulfilled by increased waste-energy desalination, the demand of alternative energy desalination reaches 14% in the fifth decade, this is more than double of the first decade.

Figure 10 shows the amount of alternative energy required to complement the gap between available water and water demand, which is converted into a number of typical 600 kW wind turbine as a source of alternative energy. In the first 15 years, less than 50 turbines are required to fill the gap with alternative energy. In the mid period, required energy increases to the equivalent of 50 to 100 turbines. In the fifth decade, it reaches between 150 and 250. This is because the demand of additional energy increases toward end of the simulation period.

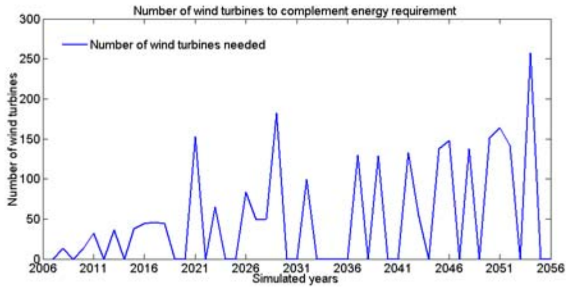

Figure 10. Example of alternative energy required

5. CONCLUSIONS

This paper presented the development of a model that uses waste incineration energy for seawater desalination to complement fresh water supply using the Gold Coast city, Australia as a case study. Our study is motivated by the successful waste incineration in Europe and Asia as well as the seawater desalination in the Middle-Eastern countries. Our model followed a dynamics systems approach with control theory combined with sub-models developed using ANN. In this paper, the calibration of the model as well as the long-term simulation including both normal year and El Niño affected years were presented. The results showed that dam water and waste energy desalinated water combined, fulfils 90% of water demand for 3 decades. Initially only 6% of water demand needs to be complemented by alternative energy source, but in the last 2 decades of the simulation, over 10% of water demand must rely on an alternative energy source. We also examined the required amount of alternative energy using a typical 600 kW wind turbines to complement the energy source as an example. Future work includes experimenting other alterative energy and possible application of the model to other cities.

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