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An artificial intelligence approach for optimizing pumping in sewer systems

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ABSTRACT

This paper presents details of a fuzzy logic system developed for the control of sewer pumping stations for energy costs savings. This is part of an ongoing collaborative project between Anglian Water and the University of Sheffield. The model rules and operation are developed for one representative pumping station in order to enable the identification of potential benefits and inhibitors to Anglian Water. Results are included that demonstrate the potential for energy cost-savings by application to a single pumping station for dry weather flow conditions and through comparison to current on/off switching rules. The fuzzy system is shown to be robust to changes in flow pattern (using both modelled inflow data and real data from a flow survey), but sensitive to changes in price structures. Application of a genetic algorithm (GA) search technique was used to adjust the parameters that define the membership functions in the fuzzy rules, in order to provide automated minimization of the energy costs towards an optimal solution. The GA system is shown to be transferable to another pumping station with different pump sizes, wet well capacity and inflow pattern. The GA solution outperformed the base case in terms of energy costs and switching totals.

Key words | fuzzy logic, genetic algorithm, sewer pumping station

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INTRODUCTION

Energy costs constitute part of the largest expenditure for nearly all water utilities worldwide and can consume up to 65 per cent of a water utility's annual operating budget. One of the greatest potential areas for energy cost-savings is the scheduling of daily pump operations (Boulos *et al.* 2001).

The UK water industry uses a total of 7,703 GWh/year in energy and spent £370 million on energy during 2007–2008. An increase in electricity usage in excess of 60 per cent was reported following the privatization of the water industry in England and Wales with a further 60–100 per cent increase (the worst case forecast being a 240 per cent increase) predicted over the next 15 years (Caffoor 2009).

Energy is Anglian Water's second highest operating cost and it forms 20 per cent of its operating budget. The energy bill for Anglian Water is £60 million a year, £32 million of which is attributable to wastewater operations comprising £23 million in treatment and £9 million in networks.

It is speculated that wastewater collection and treatment systems could benefit from many energy saving measures; derived from simple field testing and validation to improved service and maintenance of equipment, through to the use of computer control and optimization.

The cost of energy is often related to the time of day at which the energy is used. In order to promote the use of off-peak energy and hence provide smoother loading of energy production facilities, different energy rates have been introduced by many energy providers. Such a structure leads to peak-period energy usage being penalized with higher rates.

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So, avoiding peak hour pumping is one of the ways to reduce energy costs and thus reduce operational costs for wastewater system operators.

Ideally, sewerage systems are designed to be drained by gravity; however, pumping stations are often required – depending on topology, ground conditions, the location of sewage treatment works and other factors. Such pumping stations are typically controlled via classical on/off switching based simply on the fluid level in the inlet wet well. Such local control can lead to poor performance across a variety of performance indicators, including energy costs, hydraulic performance and efficiency. It is a major challenge to improve on classical switching and to optimize energy and cost efficiencies, necessitating the development of a control system capable of recognizing and responding to the complex, highly nonlinear behaviour of sewerage systems. This applies both to the more predictable dry weather conditions and also the hugely diverse flow conditions brought about by wet weather events.

CURRENT PUMP SWITCHING

A sewage pump station consists of a wet well that holds waste water and a number of pumps whose task is to empty the wet well in accordance with the control programme executed by a programmable logic controller (PLC). There are typically two main pumps (the 'duty' and 'assist' pumps) which are used in alternation. When additional flow occurs, the assist (second pump) will be turned on. Possibly a third ('storm pump') can also be used, usually to manage higher flows from wet weather events. The control strategy currently used predominantly by Anglian Water, and most other UK water service providers, to control sewage pumping is a simple on/off control system based on the fluid level in the wet well. This control is local to the pumping station and there is neither a control link between pumping stations nor any remote control available for the pumps in the pumping station. Local PLCs start or stop the pumps based on sensors or float switches detecting the level within the wet well, using predetermined set points. The PLC generally uses the following control logic algorithm: wastewater accumulates in the wet well until the liquid reaches the duty pump switch on level and then the duty pump is started. It runs on until the switch off level in the wet well is reached. The assist pump is started if the duty pump is unable to prevent incoming flow causing the liquid level to rise in the wet well. At a predetermined higher level the assist pump switches on. The pump duty assignment is cycled between the pumps, ensuring that both pumps are used approximately equally (based on operational hours, the number of pump starts or a pump failure).

ARTIFICIAL INTELLIGENCE IN THE WATER INDUSTRY

Artificial intelligence (AI) or soft computing techniques have been found useful for handling highly nonlinear systems (Chen *et al.* 2001). Such techniques consisting of fuzzy logic controls, grey modelling, genetic algorithms (GA), rough sets, artificial neural networks (ANNs), and any type of hybrid control systems, represent the progress in different paradigms of AI.

In process control, fuzzy controllers can be applied to almost any kind of processes but their characteristics make them particularly suitable for controlling time-varying, ill-defined and nonlinear systems (Fiter *et al.* 2005). Fuzzy control methods based on fuzzy sets have been widely applied to many fields and reported to show performance similar to skilled experts (Sugeno 1985).

Within the field of water and waste water engineering, soft computing techniques have been explored in different applications, for example, determining pumping rates in sewer pumping station (Yagi & Shiba 1999); an ANN for state forecast of a pump station and fuzzy inference system (FIS) to synthesize a closed loop control of sewerage pumping (Chen *et al.* 1992); Sugeno (1985) provided an extensive review of studies into the use of fuzzy control and examples of industrial applications, including the water industry. A wide range of ANN and fuzzy logic (FL) applications in the field of water resource management has been investigated in the IHE-STOWA joint research project (Lobbrecht *et al.* 2002).

There has been some application of AI techniques for pump control in sewerage systems, such as avoiding floods and reducing the discharge of pollutant loads to receiving waters (Yagi & Shiba 1999) and achieving set point wet well level control (Chen *et al.* 1992). However to date there hasn't been any work looking into the problem of saving costs (or reducing the amount of pump switching). The majority of AI applications associated with energy saving have been developed for water distribution systems and are not transferable to sewerage systems.

Fuzzy logic

Fuzzy logic is used mainly in control engineering. In 1965, Zadeh proposed the theory of fuzzy sets because of his dissatisfaction with increasing precision in control theory (Zadeh 1965). Later, fuzzy logic control research was stimulated by Mamdani's pioneering work (Mamdani 1974), which had been motivated by Zadeh's two papers on fuzzy algorithms (Zadeh 1968) and linguistic analysis (Zadeh 1973) and is in widespread use today (Shieh *et al.* 1999).

Fuzzy systems are based on linguistic, imprecise approaches to describing complex systems. They don't demand knowledge of mathematical modelling. For this reason, fuzzy controllers provide effective alternatives to classical or state–space controllers (Homaifar & McCormick 1995). A fuzzy system is fully defined by its membership functions and rule sets (Arslan & Kaya 2001). Membership functions represent the degree of belonging over a specified range [0, 1]. Input variables are partitioned into overlapping sets and each of these sets represent a membership function. Each membership function imitates a linguistic approach which is used to describe some condition in every day descriptive usage (high, low, etc). These fuzzy sets are often triangular or trapezoids. The rule set is based on fuzzy logic reasoning which employs linguistic rules in the form of IF {condition}–THEN {action} statements. There is a relationship between membership functions and rule sets. The membership values control the degree to which each of the IF–THEN rules will 'fire'.

Fuzzy logic and fuzzy control feature a simplification of a control methodology description. This allows the application of 'human language' to describe the problems and their 'fuzzy' solutions. In many control applications the model of the system is unknown or the input parameters are highly variable and unstable. In such cases, fuzzy controllers can be applied. These are more robust and are cheaper than conventional proportional-integral derivative (PID) controllers, which won popularity with their ability to stabilize and control around 90 per cent of existing processes (O'Dwyer 2003). It is also easier to understand and modify fuzzy controller rules, which not only use a human operator's strategy but are expressed in natural linguistic terms (Kalogirou 2007).

Genetic algorithms

Genetic algorithms (GAs) can be used to solve both constrained and unconstrained optimization problems. A genetic algorithm simulates the Darwinian theory of evolution using highly parallel, mathematical algorithms that transform a set (population) of mathematical objects (typically strings of ones and zeros) into a new population, using various operators such as: reproduction, mutation and crossover. At each step, the GA selects individuals at random from the current population to be parents and uses them to produce the children for the next generation. Over successive generations, the population 'evolves' toward an optimal solution. GAs and their properties are widely described in the literature (Goldberg 1989) and are the best known and most widely used global search technique with an ability to explore and exploit a given operating space using available performance measures (Herrera & Magdalena 1999). They are not guaranteed to find the global optimum solution to a problem, but they are generally good at finding acceptably good solutions to problems acceptably quickly. GAs don't use differentiation but they use function evaluation in order to find a problem solution. Thus, GAs are able to solve a wide range of problems: linear, nonlinear discrete, discontinuous, etc. (Homaifar & McCormick 1995). These reasons have contributed to the fact that, during the last few years, GA applications have grown enormously in many fields (Herrera & Magdalena 1997).

Within the field of water and waste water GAs have mainly been used to solve the problems of pipe network optimization (Dandy *et al.* 1996) and minimization of water distribution network design costs (Savic & Walters 1997). Rauch & Harremos (1999) report a number of applications of GAs for rainfall-runoff calibration problems. Mackle *et al.* (1995) used a simple GA for pump scheduling in a water supply system their objective was to minimize the costs of pumping by taking advantage of low cost electricity tariffs and additional storage in the system. In Hajda *et al.* (1998), GAs were used in combination with ANNs for applications in wastewater systems control. As GAs are likely to perform too slowly for online application, ANNs were trained to approximate GA results (learning to map the inflow forecast to the control decision). Boulos *et al.* (2001) developed an optimal operation model for real-time control (RTC) of a complex water distribution system with the objective of minimizing the costs of energy consumed for pumping. GAs were used to automatically determine the optimal pump operation policy for each pumping station in a water distribution system to meet target hydraulic performance requirements. This review indicates some of the potential of GAs, but also highlights that attention has focused on water distribution systems with little application to sewerage systems.

Tuning fuzzy logic systems

Fuzzy controller performance is determined by its control rules and membership functions. For this reason it is very important to adjust these parameters to the controlled process.

The automatic definition of a fuzzy system could be considered in some cases as an optimization or search process. Different approaches can be found in Herrera & Magdalena (1997). Previously, the generation of membership functions has been achieved mainly manually by expert judgement or by trial and error. A GA would appear to be a natural candidate for this task as it will generate a fuzzy logic controller which should perform optimally. Cordon *et al.* (1995) contains a bibliography of different applications combining GAs with fuzzy logic. One half of the 345 listed references are specific to the design, tuning, learning and applications of fuzzy logic controllers. GAs have been used for the adjustment of membership function parameters (Karr 1991; Meredith *et al.* 1992; Lee & Takagi 1993), as they offer a convenient way to adjust membership functions. There are similar reasons for using GA to produce the rules set (Homaifar & McCormick 1995). These tasks can be done separately. Karr & Gentry (1993) used GAs to generate membership functions for a pH control process and Karr (1991) for the cart-pole problem (Barto *et al.* 1983). Fuzzy rule bases have been tuned by GA, for example Yagi & Shiba (1999) for determining the pump rates of combined sewerage pumping station. Arslan & Kaya (2001) proposed a method for the determination of membership functions by GA, suggesting that a GA can find the optimum solution without looking at the shape of membership functions and can be used for any membership function with known mathematical model. Homaifar & McCormick (1995) presented the idea that membership functions and rule sets are co-dependent and that only through the simultaneous design of membership function and rule sets for fuzzy controllers it is possible to use the GA to its full advantage and obtain an optimal solution.

This application

In this paper, an automatic control methodology for sewer pumping stations utilizing fuzzy logic is proposed. A fuzzy logic rule set is used to balance pumps, that is, to decide the combination and timing for pump operation in each pumping station avoiding peak hour pumping as one of the ways to reduce energy usage. MATLAB based software (using the fuzzy logic and GA toolbox) has been developed and the feasibility of the approach explored through simulation. Additionally, automatization of the fuzzy inference system (FIS) generation was explored. GAs were used in order to determine Membership functions (MFs) for the FIS. The shapes of MFs were predetermined and the GA was used to determine the base lengths of the MFs and the locations of the peaks. Work is presented for dry weather conditions only.

CASE STUDY

Anglian Water are currently conducting a project within the Cliff Quay catchment, Ipswich, entitled ‘Sewernet’. The project has the overall objective of improving the operational performance of sewer networks. The philosophy for the project is to identify opportunities for the optimization of a sewer network using a combination of the most appropriate sensing technologies, data communications techniques and analytical software in the context of the current system configuration and operating parameters. The idea is to enable a level of automated control with advisory outputs suitable for operational staff to be made aware of the status of the system in a ‘real-time’ environment. An understanding of the existing sewer network provides a platform for analysis of sensor data using predictive, adaptive software linking system performance requirements, load profiles, system capabilities, and control and management arrangements to enable optimal effective use of the system. In the context of the 'Sewernet' project to which this work is linked, it can be seen that the development and use of a pump control system using artificial intelligence techniques underpins and cements strongly the 'Sewernet' philosophy.

The Cliff Quay catchment can be considered as consisting of four areas: the low level sewer, the high level sewer, Eastern area trunk sewer and South East area sewer. It is fully combined in the centre, whereas the East and North-West are virtually separated. The so called low level sewer is partially combined and has 13 pumping stations. This research is focused on monitoring a sub-set of the whole catchment: the first six in-line pumping stations in the low level sewer subcatchment. Most stations have two or three pumps.

As the first step in on-going research, a fuzzy logic based control system for one representative site – Sproughton Road SPS – was developed. There are three fixed speed pumps in this pumping station: duty, assist and stand-by. The duty pump has a maximum discharge of 0.043 m^3/s and power of $P = 4.7$ kW. The second pump, assist pump, has a maximum discharge of 0.013 m^3/s and power of $P = 1.6$ kW. The standby pump is a duplicate of the assist pump, present to facilitate maintenance only, and is not considered further here. In Sproughton Road SPS the levels for the classical on/off pump switching are as follows: for pump 1, the switch off level is 1.1 m and switch on level is 1.95 m; for pump 2, the switch off level is 2.1 m and switch on level is 2.5 m. The wet well is 6.1 m high with varying base area of 7 m^2 (from ground level to 1.1 m height) and 8.4 m^2 (from 1.1 m to 6.1 m height). The wet well has an overflow at 3.52 m. The station is fitted with an ultrasonic level meter providing regular data on the water level in the wet well.

This pumping station is the first pumping station in the study area and has a clearly defined gravity driven associated drainage area. Hence it was possible to simulate its operation independently from other pumping stations. The study area schematic is shown in Figure 1 (square box represents flow monitors).

Fuzzy inference system (FIS)

A FIS takes user determined inputs and through the use of membership functions and rule sets provides certain outputs. For this application the selection of the input variables has to be done in a way that enables the FIS model to accomplish the task of generating a pump switching pattern. Two input variables were chosen to be used by the FIS. The input variables of the FIS are: the rate of change (RC) – the change of level in the wet well between two sample intervals ($T = 5$ min) and the level (L) in the wet well. The output variable is change in control (dU), that is, the number of pumps to be started or stopped. These variables were selected because there is a lack of available recorded data about SPS and there is a level sensor in Sproughton Road SPS wet well, as is the case for most SPS.

To deal with these variables, fuzzy labels for membership functions (MFs) have been introduced, an example of which is shown in Figure 2. For the rate of change MFs the labels are: negative big (NB), negative small (NS), zero (Z), positive

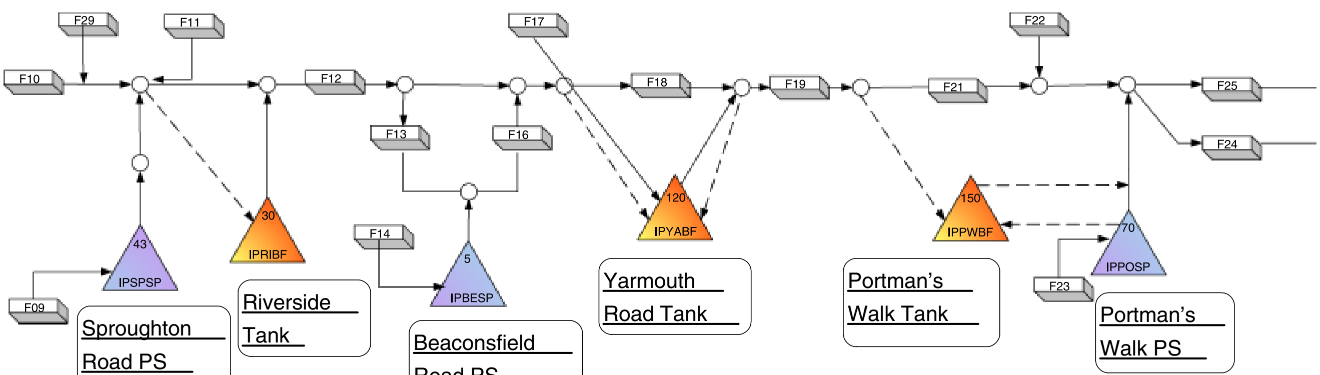

Figure 1 | Cliff Quay catchment –▲ represents a pumping station the study area.

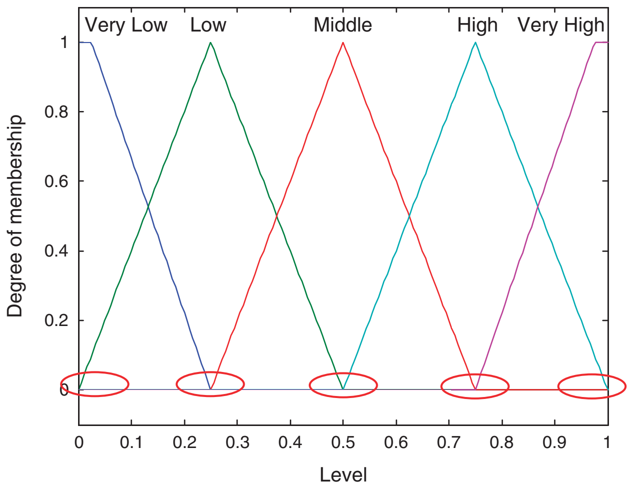

Figure 2 | Membership functions – level in the wet well.

big (PB) and positive small (PS). For the variable L the MFs labels are: very low (VL), low (Lo), middle (M), high (H), very high (VH). The minimum value is zero and the maximum value is 1 for both variables, which equates to 0 and 100 per cent, respectively. The intension was to provide generality for the FIS, such that the same FIS can then be used for different pumping stations regardless of dimensions of the wet well. The output variable change of control (dU) has membership function labels as follows: '−2' (stop two pumps), '−1' (stop one pump), '0'(don't change the state of the pumps), '1' (start one pump), '2' (start two pumps).

In this paper, the FIS system consists of three separate FIS, each for a different energy tariff used within Anglian Water: normal, low and high. Each of them has a different rule base and input membership functions but they all have the same output with identically defined membership functions.

Fuzzy control rules are expressed in the form of IF–THEN using fuzzy labels. For example: IF (RC = NB) AND (L = VL) then (dU = 0). Where RC and L are input variables and dU is the output variable. This rule means: 'If the rate of change of level in the wet well (RC) is negative big (NB) and the level in the wet well (L) is very low (VL) then control change (dU) is 0' (both pumps remain in their present states). Pump state (run or idle) is thus determined by the FIS responding to input variables, rate of change of level and the level in the wet well.

The FIS control model was developed with the MATLAB Fuzzy Logic toolbox. The FIS uses the Mamdani method (Mamdani & Assilian 1975). The FIS used here applies the min-max-centroid method. In each rule a minimum value is selected among the inputs (RC and L) membership functions involved in the IF-part. In this way the strength of the rule is formed which defines the intensity of the membership function of the output variable involved in the THEN-part. Output membership functions of every rule are combined by the maximum value. The output value for dU is calculated by using the centroid method for defuzzification. The FIS output is a crisp value but not an integer, post processed as needed. The output value is rounded to an integer [−2, 2].

Table 1 provides the rule base for the normal tariff as an example. The aim was to design a control system which will make energy cost-savings by using the best time (with associated low-cost tariff) to operate the pumps. During the high tariff, the control strategy could be summarized as 'don't pump, unless you have to'. Based on information on the time of day, one of the three FISs is used for control.

RESULTS

In order to evaluate the effectiveness of the FIS control system, in terms of reducing energy costs, results for the manually tuned FIS control system were compared with a model (base case). This base case implements the current on/off (industry standard) set of rules for control of Sproughton Road wastewater pumping station. The same values for the inflow to the pump station wet well and the same tariffs were used in both cases. The inflow hydrograph is for a 24 h period at 5 min resolution. This was extracted from an Infoworks hydraulic network model of the study region for dry weather

Table 1 | Rule base for normal tariff

		Level				
		VL	L	M	H	VH
Rate of change	NB	0	1	1	2	2
	NS	0	0	1	1	2
	Z	−2	0	0	0	2
	PS	−2	−2	0	0	0
	PB	−2	−1	−1	0	0

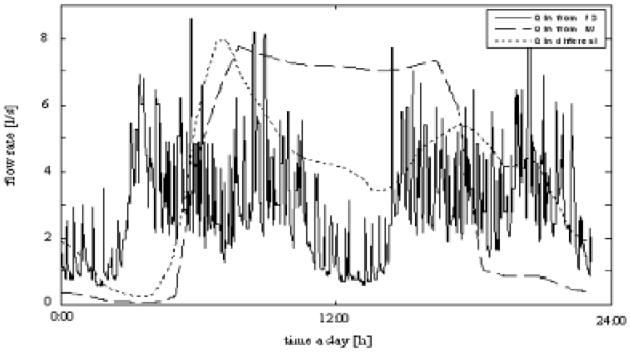

Figure 3 | Different inflow patterns – Qin base inflow pattern (dashed line), more representative inflow pattern of a domestic dominated catchment (dotted line) and inflow data from a flow survey (solid line).

conditions. Figure 3 shows this pattern (dashed line), from which it will be seen that the area served by this SPS is not a typical domestic diurnal pattern, rather an industrially dominated area. In all cases the 24 h pattern is 'looped' until repeatable start and end wet well levels are achieved such that there is not any net loss or gain in volume in the wet well, which could result in an apparent loss or gain in pumping volume and hence energy use. While a modelled incoming flow pattern has been used for comparison purposes, in practice the system could be driven directly by the ultrasonic level data.

Figures 4 and 5 show patterns of the level in the wet well, rate of change and pump switching pattern for the base case and the manually tuned FIS. The manually tuned FIS was designed with the goal that the level in the wet well should be maintained as low as possible during the low tariff and as high as possible during the high tariff. In the base case (Figure 4), there is a poor use of the wet well (30–50 per cent) and tariffs are taken into account. In the manually tuned FIS (Figure 5), there is a good use of the wet well (15–90 per cent during the normal tariff); low level in the wet well is maintained during the low cost tariff and high level during the high cost tariff.

The first row of Table 2 provides the base case and the manually tuned FIS output results in terms of energy used, showing a modest 1 per cent saving. The assumed costs of energy for each pump in both cases are calculated based on tariff costs of: low tariff 3.38 p/kWh; normal tariff 4.86 p/kWh; high tariff 5.44 p/kWh.

Robustness of FIS to inflow conditions

The proposed FIS control system needs to be robust to cope with changes and uncertainty in flow, which will change on a daily basis even for dry weather conditions. Such robustness in dry weather conditions is important due to the unpredictable wastewater generation behaviour of customers, and the likely inaccuracies of idealized hydraulic modelling results. Robustness was tested with changed inflow patterns: a) base inflow (Figure 3, dashed line) ± 10–40 per cent of its original value, b) change in peakedness and c) different inflow pattern (Figure 3, dotted line) more representative of a domestic dominated catchment.

Table 2 illustrates the ability of a FIS system to provide satisfactory control for different inflow patterns. In all of the presented cases the FIS shows 1–4.3 per cent energy cost savings and a less or equal number of pump runs. The

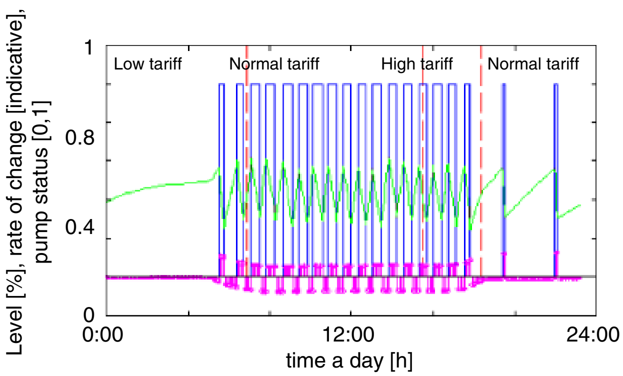

Figure 4 | Base case – Level in the wet well (solid line), Rate of change (line with rounded head), Pump switching (vertical lines).

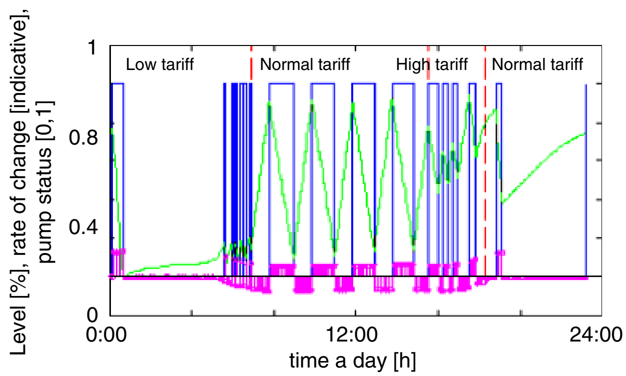

Figure 5 | Manually tuned FIS – Level in the wet well (solid line), Rate of change (line with rounded head), Pump switching (vertical lines).

Table 2 | Example of use the base case and FIS to control a single SPS for different inflow patterns

	Base case		Manually tuned FIS		
	Energy cost [p/day]	Number of starts in 24 hours	Energy cost [p/day]	Number of starts in 24 hours	Cost savings [%]
Qin	**56.2320**	**19**	**55.6960**	**17**	**1.0**
Qin + 10% Qin	62.1413	18	61.3093	16	1.3
Qin − 10% Qin	50.3653	17	49.9067	16	1.0
Qin + 20% Qin	67.4800	17	66.5147	16 + 1	1.4
Qin − 20% Qin	44.8853	18	44.1387	11	1.6
Qin + 30% Qin	73.2696	17	72.2267	17 + 1	1.4
Qin − 30% Qin	39.3147	17	38.3707	12	2.4
Qin + 40% Qin	79.3333	15	77.9173	16 + 1	1.8
Qin − 40% Qin	33.8773	15	32.4267	10	4.3
Peak	122.9520	3 + 20	122.2480	9 + 6	0.5
Qin different	53.2667	23	52.2027	19	2.0

concept of possible energy savings with FIS control of sewage pumping station based on the wet well inflow data extracted from the model was hence proved. Additionally, the FIS system resulted in less number of pump switch per 24 hours, with possible savings in pump wear rates. It is an important finding that the FIS is robust to changes in the flow pattern, as such changes will occur on a daily basis in an unpredictable fashion.

Robustness of FIS to changes in energy tariffs

The manually tuned FIS robustness was also tested in case of the likely price changes of electricity tariffs. These typically vary at different times of the year and are reviewed and adjusted by energy supply companies on at least an annual basis. The robustness of the manually tuned FIS was tested for two further tariffs (in addition to the tariff used for the Table 2 results) provided by Anglian Water. These were for different periods during the year.

(a) Increased rates – low tariff 5.66 p/kWh; normal tariff 7.08 p/kWh; high tariff 12.10 p/kWh.
(b) Increased number and rates of high tariffs – low tariff 5.71 p/kWh; normal tariff 7.01 p/kWh; high tariff (the first hour) 12.04 p/kWh, (the second hour) 20.96 p/kWh, (the third hour) 10.78 p/kWh.

From Table 3 it can be seen that the manually tuned FIS model is not necessarily robust to changes in energy tariff

Table 3 | Example of use the base case and FIS to control a single SPS with variations of the price within energy tariffs

	Base case		Manually tuned FIS		
	Energy cost [p/day]	Number of starts in 24 hours	Energy cost [p/day]	Number of starts in 24 hours	Cost savings [%]
LT = 5.66 NT = 7.08 HT = 12.10	91.5120	19	92.0747	18 + 2	−0.6
LT = 5.71 NT = 7.01 HT1 = 12.4 HT2 = 20.96 HT3 = 10.78	96.9947	19	95.2747	18 + 2	1.77

costs. This means that FIS would have to be retuned every time the energy tariff cost is altered. Changes in tariff, however, are known in advance and could be planned for, provided that a method to automatically tune the system can be developed.

Application of GA to tune FIS

The application of a GA to generate the input variables MFs of the FIS was explored. MF functions were chosen as the decision variable for the GA as during manual tuning of the FIS it was found to be sensitive to changes in MFs shapes and positions and to produce significantly different results in terms of cost savings. Conversely the rule base design was based on expert knowledge of the system and the rules followed robust logic with little room for reasonable interpretation or flexibility.

The MFs shapes were predetermined (triangles and trapezoidal) defined by five points marked with red circles on Figure 2 (locations of base points, while the peaks of the MFs were defined by the same points as base but with constraints of position included). In this way, the GA searched for 30 points (five points to define MFs for each input, two inputs for each FIS, three FIS for each tariff) to automatically tune the FIS, generating MFs in order to achieve energy cost savings.

The initial population of the GA was determined randomly. Using the FIS, the fitness value (energy costs) was computed as the objective function or minimisation criteria. The energy costs are computed from the calculated number of runs for each pump and the price decided by the time of day (tariff). In case the level is outside the predetermined limits, the penalty function is calculated and this value is added to calculated objective function. The GA stop criteria were no improvement in the objective function for a number of generations.

In this work, the MATLAB Genetic Algorithm toolbox was used. A function (the objective or fitness function) is written as a .m file which is then optimized (minimized) by the GA. This function can be described as follows.

1. Initial population is generated randomly with the constraint: $x_i < x_{=i+1}$ and $\mathrm{abs}(x_{i+1} - x_i) < 0.05$, $I = 1{:}30$.
2. Each generation in population is checked for the condition: $x_i = x_{=i+1}$ or $\mathrm{abs}(x_{i+1} - x_i) > 0.05$, $i = 1{:}30$. If it is satisfied, the penalty value for the objective function is assigned and the next generation from the population is considered.
3. Level in the wet well is calculated based on inflow/outflow in the wet well.
4. Rate of change is calculated.

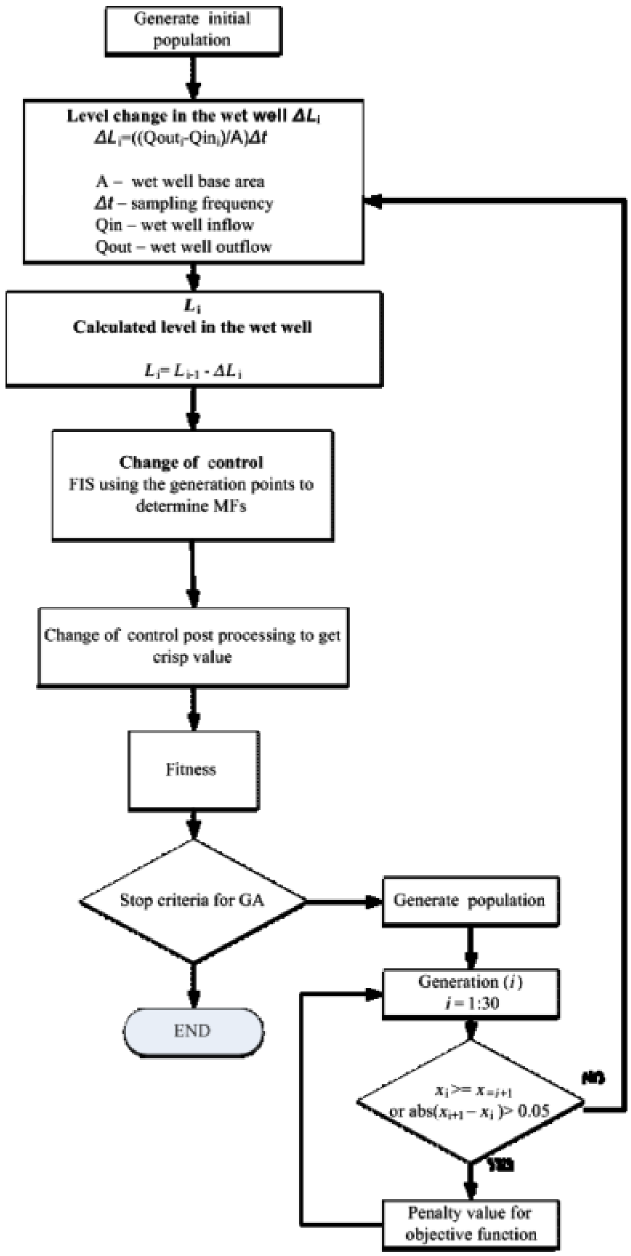

Figure 6 | Flow chart of computation.

Table 4 | Sproughton Road SPS – the comparison of energy and pump switching saving achieved by GA tuned FIS compared to manual tuned and base case pump switching rules

	Base Case		Manually tuned FIS		GA tuned FIS		Cost savings [%]	
Qin data	Energy cost [p/day]	Number of starts in 24 hours	Energy cost [p/day]	Number of starts in 24 hours	Energy cost [p/day]	Number of starts in 24 hours	Base case vs. Manually tuned FIS	Base case vs. GA tuned FIS
InfoWorks	56.2320	19	56.1467	18 + 2	55.28	16	1.5	1.7
Flow survey	42.36	98	42.0197	33	41.9557	27	1	1

5. Time of day determines FIS (tariff) to be used to calculate change of control, that is, to decide the combination for pump operation.
6. Step 2 is repeated until the 24 h level profile in the wet well is calculated.
7. Flow balance is performed.
8. The objective function is calculated using the results obtained by FIS.

The flow diagram of the FIS control system is provided in Figure 6 which also explains the software algorithm.

Table 4 presents the results of the GA tuned FIS compared with the base case and the manually tuned FIS for the Sproughton Road SPS. The GA shows better performance both in cost savings and lesser number of switches. This is significant in the case when the inflow data used was real data from a flow survey. This flow survey was undertaken by Anglian Water in May 2010 (Figure 3, solid line).

From Table 4 it can be seen that the GA tuned FIS outperformed both the base case and the manually tuned FIS for the initial flow and cost structures in terms of cost savings. It is interesting to note that the GA solution has also further reduced the number of pump switches. This is a notable result, providing potential reduced wear rates extending pump life. However this was not considered in the objective function, rather it is a result of the natural process to improve the use of the wet well capacity. The GA tuned FIS was shown to display similar robustness to changes to inflow as the manually tuned GA.

Further, the GA tuned FIS showed robustness with regards to flow changes. It out performed the base case situation with significantly less switching (three times less). The largest uncertainty in sewerage system is with flow, and the paper demonstrates robustness to this parameter.

Transferability of GA to tune FIS solution

Table 5 presents the results of the GA tuned FIS compared with the base case and the manually tuned FIS for the Portmans Walk SPS. Portmans Walk is one of six pumping station in the study area. There are two fixed speed pumps in this pumping station: duty and assist pumps. The duty pump has a maximum discharge of 0.068 m^3/s and power $P = 8.3$ kW. The second pump, assist pump, has a maximum discharge of 0.047 m^3/s and power of $P = 5.3$ kW. In the Portmans Walk SPS the levels for the classical on/off pump switching are as follows: for pump 1, the switch off level is 1 m and switch on level is 1.5 m; for pump 2, the switch off level is 1 m and switch on level is 2 m. The wet well is 7.5 m high with base area of 7.49 m^2. The wet well has an overflow at 2.45 m.

In Table 5 it is shown that using the GA system to tune the FIS solution is transferable to other pumping stations with different pump sizes, wet well capacities and inflow pattern. The GA solution outperforms the base case in terms of energy costs and switching totals.

These results are encouraging, but further research is needed to ensure that GA design of FIS performs optimally.

Table 5 | Portmans Walk SPS – the comparison of energy and pump switching saving achieved by GA tuned FIS compared to manual tuned and base case pump switching rules

	Base Case		Manually tuned FIS		GA tuned FIS		Cost savings [%]	
Qin data	Energy cost [p/day]	Number of starts in 24 hours	Energy cost [p/day]	Number of starts in 24 hours	Energy cost [p/day]	Number of starts in 24 hours	Base case vs. Manually tuned FIS	Base case vs. GA tuned FIS
InfoWorks	61.1914	168	60.4789	50	59.9129	48	1	1
Flow survey	95.0133	106	94.9582	97	94.4262	84	1	1

It is assumed that the inclusion of more points of the MFs specified by the GA (locations of bases and peaks of MFs should be independent) will lead to an improved performing FIS but may be at the expense of computational resources. Also, the design of both of the major components of a FIS, MFs and the rule base, using a GA should be investigated.

In the future this work will be extended in a number of ways such as: consideration of pump efficiency, a look-ahead functionality to take account of expected flows and tariffs, training ANNs for diurnal inflow pattern prediction and integrating FL-based control across interconnected pumping stations. It is expected that the energy and other operational efficiencies of these will build significantly on the relatively modest figures presented here. It is intended that these planned developments will be demonstrated by live trials in association with the SewerNet project with Anglian water.

CONCLUSIONS

In this paper it has been demonstrated how pump switching control may be accomplished by implementing a simple first prototype fuzzy logic control system at a single sewer pumping station. The potential for modest energy cost savings and reduced pump switching is shown with the system out performing a reference, base case. The fuzzy logic control is also demonstrated to design a robust controller which can perform well over a wide range of inflow volumes and patterns, including real data from a flow survey.

The concept that a GA can be applied to automatically tune the fuzzy logic controller, by generating its MFs, in order to achieve energy cost savings was explored. This was shown to provide improved energy and pump switching savings over the manually tuned system but without the previously needed expert knowledge.

The GA system was shown to be transferable to another pumping station with different pump sizes, wet well capacity and inflow pattern. The GA solution outperformed the base case in terms of energy costs and switching totals.

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