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Demand Side Management of an Urban Water Supply Using Wholesale Electricity Price

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Abstract

Municipal water supply consumes large quantities of electrical energy to move water from catchment areas to service reservoirs near centres of population. Pumping does not necessarily occur round the clock, but rather when necessary to uphold constraints relating to reservoir levels and system pressure. There is a degree of flexibility in the timing of pumping that makes it an excellent candidate for Demand Side Management, meaning that it can provide opportunities for improving power system operation and reducing electricity costs for the water utility. The extent of this flexibility depends on a number of factors. This study examines the optimisation of two water supply systems - the 'Van Zyl' benchmark system and a representation of the supply for the city of Belfast, Northern Ireland. The potential to employ intelligent operation of pumps to help bolster uptake of variable wind generation is assessed, as is quantification of the potential savings for a water utility. The results show significant potential savings for the water utility as well as a substantial increase in the utilisation of wind power.

Keywords: Demand Side Management, Real Time Pricing, Genetic Algorithms, Wind Energy, Renewable Energy, Optimisation, Water Pumping

Nomenclature

i	Time period (i = 1,2, ... 24, 60 min/period)
m	Mourne supply
n	Lough Neagh supply
d	Inside pipe diameter (m)
h_f	Head loss (m)
C	Hazen-Williams pipe roughness coefficient
L	Pipe length (m)
Q	Volumetric flow rate (m^3/s)
E_i	Electricity cost, i^{th} period (£)
W_i	Wind generation as % of total in i^{th} period
$F_{p,i}$	Pump p flow rate, i^{th} period (l/s)
M_i	Energy cost per unit, i^{th} period (£/kWh)
$D_{p,i}$	Flow from service reservoir p, i^{th} period (l/s)
$P_{p,i}$	Pump p energy consumption, i^{th} period (kWh)
$R_{p,i}$	Service reservoir p water volume, i^{th} period (l)
$R_{p,max}$	Maximum water volume, service reservoir p (l)
$R_{p,min}$	Minimum water volume, service reservoir p (l)

1. Introduction

The drive to phase out fossil-fired generation has increased investment in renewable generation. In Northwest Europe, wind is an abundant renewable resource [1], and, as such, significant efforts have been made to increase the penetration of wind generation in power systems.

Ireland, although composed of two political jurisdictions (the Republic of Ireland and Northern Ireland), has one synchronised power system and Single Electricity Market (SEM). The Irish power system supports a relatively small population of 6.5 million people and has 750 MW of HVDC interconnection with Britain [2]. A target of 40% of all electricity is to come from renewable sources by 2020, predominantly from wind power [3]. This target causes some issues for the Irish system, some of which are unique due to its relative isolation and limited available interconnection.

Modern wind turbines, unlike traditional synchronous generators, do not provide inertia to the power system as their rotating masses are connected to the grid through power electronics. Significant power system inertia mitigates frequency transients during system faults

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and large disturbances [4], and hence it is necessary to maintain a minimum level of system inertia. Unlike other countries with high penetrations of wind power (such as Denmark), Ireland has only limited HVDC interconnection, which provides no inertial support. Because of this constraint, System Non-Synchronous Penetration (SNSP) is currently limited to 55% on the Irish power system [5], with any renewable generation above this level wasted. Due to its variable nature, wind power is non-dispatchable apart from curtailment by a system operator.

In order to meet the high targets for wind power integration, it is estimated that the SNSP limit would have to be raised to 70% to avoid excessive curtailment [2]. This will be a significant challenge, especially for conventional generators [5], but presupposes that generation must be varied to meet a varying demand beyond the operator's influence. Under this regime, the system operator would have more problems when controlling a power system with high penetrations of wind power than one without. Dispatchable generation would see much greater variation in output in order to address wind variability, which is undesirable as it prevents generators operating at their most efficient settings.

Demand Side Management (DSM) provides a means of mitigating the regulation duty of conventional generation. DSM has traditionally been seen as a method whereby a system operator or utility would exert direct control over load [6]. The main contribution of this work is in investigating whether market-driven DSM can provide improvements in wind power utilisation to the power system without explicit system operator intervention, but rather by the load responding to changes in system price. This is the first study to optimise a water network on the basis of Real-Time Pricing (RTP) and quantify both the energy cost savings and wind power utilisation.

2. Scope for Optimising Water Supply

2.1. Demand Side Management

With DSM, supply of managed load is encouraged when net demand (consumer demand less renewable generation) is low. The incentive is the lower cost of electricity at such times. Conversely, the supply of managed load is discouraged when net demand, and electricity price, are high. The boost to net demand when renewable generation is plentiful eases the SNSP constraint.

DSM is regarded as an important part of the future operation of power networks and as such has been the focus of a number of studies. Where DSM has been carried out based on energy cost, it has primarily been on the basis of Time of Use (ToU) pricing [8][9][11]. These are multi-rate tariffs which change several times a day. Although promoting energy use during off-peak times, ToU tariffs do not track the actual market price of electricity and thus do not provide an incentive for consumers to respond to specific events, such as generator outages or high-wind scenarios. ToU tariffs reflect only the general trends of electricity cost and usually have no more than four changes per day. Increased penetrations of variable generation such as wind generation mean that price peaks do not always occur at the same time of day, as high penetrations of low marginal cost generation during peak times reduce the need for low merit generation, thus reducing market prices. ToU tariffs do not reflect these day-to-day variations. An RTP tariff, based on the wholesale cost of electricity, offers a realistic means of tracking the variation in system price.

RTP-based DSM has been implemented in [12]-[15] with significant savings in energy cost. Finn *et al.* in [14] optimised residential load on the basis of RTP and saw increases in wind power utilisation of up to 23.3%, while in [15], RTP-based optimisation of industrial loads saw wind power utilisation increase by 5.8% while also reducing energy cost.

A common theme is the aggregation of flexible residential loads through the use of smart meters and a central controller in order to minimise decision making and maximise savings [7]-[9]. Such schemes have the disadvantage of involving a large number of stakeholders (residential consumers) who must voluntarily submit to having their energy consumption controlled externally. However, the potential has been shown for significant savings in energy costs for consumers. Vanthournout et al. in [10] found that it was difficult to maintain involvement of residential consumers in RTP schemes due to response fatigue - automation was required in order to make it viable.

DSM has also been demonstrated as being viable for provision of balancing reserve for wind generation [9].

Industrial loads frequently have a higher degree of operational flexibility than residential loads [13],[15]. Industrial consumers represent 42% of global electrical consumption. Industrial units are large compared to residential or commercial loads and are centrally controlled and owned, reducing the complexity of co-ordination and thus making them very attractive for DSM [16]. In [13], DSM of aggregated residential load was compared with that of representative commercial demand and a number of typical industrial processes. A

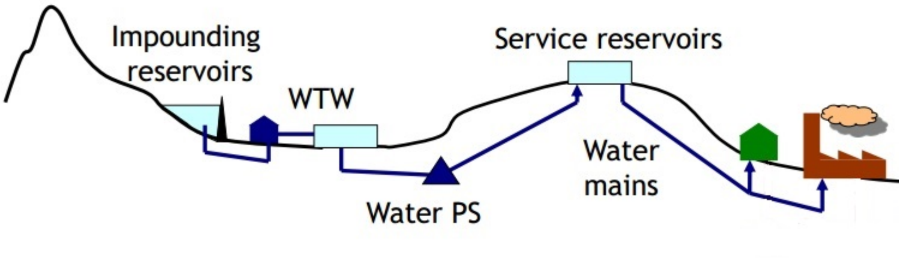

Figure 1: *Layout of a water supply network*

10% saving in energy costs was seen with the industrial DSM, compared to 5.8% for commercial and 5% for residential. Similarly high savings were also seen in [12].

2.2. *Public Water Supply*

Public water supply is an excellent candidate for the application of DSM due its significant potential for a large number of operating modes. Water networks are centrally owned and controlled and would require minimal modification to allow optimised operation.

Water pumping can be classed broadly as an interruptible load. In [16], a steel mill was optimised on the basis of several smart pricing scenarios. Under each pricing model, optimal scheduling resulted in higher profit, although higher profits were seen with ToU pricing compared to RTP - the steel mill which was modelled operated on a batch cycle, meaning that once a batch started it could not be interrupted - making it less suitable for taking advantage of the higher level of variability of RTP compared to ToU pricing. Water pumping can be interrupted, provided reservoir level constraints are maintained and wear from pump switching is considered. The basic layout of a water supply system can be seen in Fig. 1. Large, centrally controlled pumps are used to move water from catchment areas to service reservoirs (SRs) near centres of population, from which water flows to consumers. The hydrostatic head of these SRs is used to maintain system pressure and, as long as SR water levels are maintained between minimum and maximum levels, there is a high degree of flexibility over the timing of pumping. The electricity demand of Northern Ireland Water (NIW) accounts for approximately 3% of all electrical demand in Northern Ireland, a figure representative of water supply systems worldwide.

NIW oversees 26,700 km of water mains, supplying 563 million litres of water per day to 1.8 million people. A total of 23 impounding reservoirs supply more than 370 supply reservoirs [17].

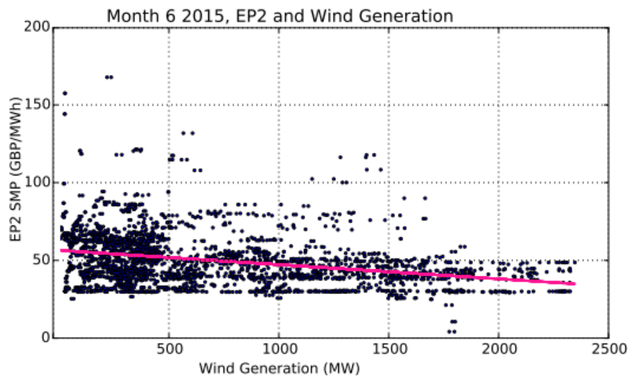

Figure 2: *SMP and wind generation, June 2015*

Many of NIW's facilities are run on ToU tariffs. NIW have carried out basic optimisation at some of their pumping stations in the past, trying to carry out as much pumping as possible during low-price periods.

In the SEM, System Marginal Price (SMP) changes every 30 minutes and reflects the operating cost of the single most expensive generator required to fulfill demand [20]. The higher the penetration of wind generation on the power system, the lower the requirement for expensive generation. Since wind is considered to have no marginal cost, higher wind penetrations should result in a lower system cost. Fig. 2 shows the final SMP plotted against wind generation for one month in 2015. It is clear from this graph that there is some degree of correlation between wind and SMP: this can be explained by the current conservative operation of the power system. When wind penetrations are high, marginal generation is not decommitted but rather dispatched down. This policy, though resulting in generators running at low efficiencies, gives the system operator a margin for error with regard to wind forecasting uncertainty. At very high wind penetrations such a policy would not be justifiable.

SMP-based optimisation of load would nonetheless help to flatten the demand curve, as it would promote operation during low demand and low price scenarios while discouraging consumption during peak periods.

There are several different 'versions' of SMP. The actual price paid to generators (termed as Ex Post 2 or EP2) is not published by the SEM Operator (SEM-O) until four days after the day in question (D+4). A full day forecast (Ex-ante 1, EA1) is made available at 11:00 one day before actual trading. This is updated at 16:00 with the Ex-Ante 2 or EA2 forecast, and again at 9:30 on the day itself with the Within Day 1 (WD1) forecast [21]. It is on the basis of these forecasts that pumping optimisation is proposed in this work. Optimising demand on the basis of the forecast wholesale price of electricity could provide a means to increase the uptake of wind generation by encouraging demand when wind generation is high as well as minimising the price paid by the consumer.

In [14], Finn *et al.* carried out a 6-month study on a domestic dishwasher, optimising operation based on EA1 and EP2 SMP. EP2 optimisation saw energy cost decrease by more than 20% and wind power utilisation increase by 23.5%, while EA1 optimisation saw a 17.5% reduction in cost and wind power utilisation increase by 16.9%. The inherent uncertainty of price forecasting means that it would be almost impossible to make the savings seen in the EP2 scenario. This study found that scheduling load on the basis of the EA1 forecast was a viable way to reduce energy costs and improve wind power utilisation.

In [22], Paudyal *et al.* applied an industrial load management model to a simplified representation of a water pumping facility, based on one day of data relating to an RTP tariff in Ontario, Canada. A 38.1% decrease in energy costs compared to non-optimised operation was observed. This simulation, although short in duration and disregarding hydraulic constraints, is notable in that it considers the impact of water pumping optimisation on the power system, citing its implementation as a means by which system operators could reduce peak demand.

DSM of water networks is cost effective and technically feasible, and price based optimisation of water networks has been carried out in the past [22]-[30].

3. Optimisation

Various methods have been proposed for pumping optimisation, including linear programming [23], non-linear programming [24] and dynamic programming [25]. Heuristic methods, particularly Genetic Algorithms (GAs), have been used successfully in a number of studies, as they avoid the combinatorial explosion inherent in other methods [27]-[30].

GAs are meta-heuristic algorithms which simulate evolution and natural selection to select solutions in a given generation based on a measure of fitness (the *fitness function*). The algorithm initialises by randomly creating a population of potential solutions. The fittest solutions in each generation are bred with each other (*crossover*) to create the next generation. An individual solution's chance of survival is proportional to its fitness. Random mutation is employed in order to diversify the population and reduce the likelihood of convergence to a non-global optimum [31]. Mutation and crossover are controlled by predefined probabilities. There are a number of different ways of defining how many individuals survive from one generation to the next - elitism was used here to ensure that the fittest individual in a given generation was carried forward to the next.

4. Water Network modelling and specification

In this work, the pumping schedules of two water supply systems were optimised - the 'Van Zyl' benchmark network, first proposed in [27], and the high-level supply of the city of Belfast, Northern Ireland. Optimisation was carried out using the 'pyevolve' toolkit in Python, integrated with the EPANET water network modelling software [26]. Potential solutions were generated by a GA, which were then evaluated for violation of hydraulic constraints in EPANET before being passed back to the GA to evaluate reservoir level and maximum daily flow constraints. Feasible solutions were scored on the basis of the optimisation objective (fitness function), depending on the scenario.

4.1. 'Van Zyl' benchmark system

The 'Van Zyl' test system was first used by Van Zyl *et al.* in [27] and has been frequently used as a benchmark system for testing optimisation algorithms and investigating new operating procedures. It consists of a reservoir supplying two tanks (at different altitudes) via two primary pumps and one boost pump (see Fig. 3, full system specification in [27]). Demand

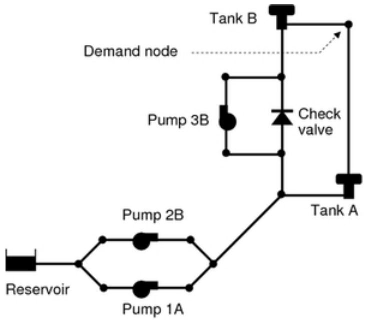

Figure 3: *'Van Zyl' test system*

is taken from one node situated between both tanks. There are a large number of potential operating modes for this system, making it an excellent candidate for optimisation and testing of algorithms. Pump power varies slightly depending on the system pressure, but the primary pumps have an operating power of up to 200 kW while the boost pump consumes up to 50 kW.

4.2. Belfast System

The largest component of NIW's supply network is that of the city of Belfast. A model of the Belfast water supply system was developed using data made available by NIW. Belfast is a medium-sized city of approximately 500k inhabitants, who each consume 360 l/day of water on average [17]. Belfast's water supply system is representative of water supply systems on the island of Ireland, where the power system data from this study was taken.

The Belfast water network has a number of interesting characteristics. Most of the city's water supply comes from two catchments: the Mourne mountains to the South, and Lough Neagh to the Northwest (Fig. 4). The pumps at Dunore Point (part of the Lough Neagh supply) operate against a greater hydraulic head than those of the Mourne Conduit. Because of this, energy consumption of the Lough Neagh supply is higher than the Mourne supply. However, there is a limit of 130 Ml/day on abstraction from the Silent Valley reservoir in the Mournes, ensuring that both the Mourne and Lough Neagh supplies are always available to provide Belfast's water. Details of both sources can be seen in Table 1.

Data for the Belfast system were obtained from NIW's Asset Management division, as well as from Ordnance Survey maps and NIW press releases [18]-[19],[32]. Due to the difficulty with accessing specific data on system operation, a number of approximations were necessary. Service reservoir capacities were inferred from satellite data, while pump power was calculated from pump flow rates and system head. Pumps were modelled as single-speed units. The water supply of Belfast is not isolated from the rest of the Northern Ireland network, and a small proportion of the water carried is diverted to other areas. In order to reduce the computational complexity of the model this off-take was ignored, and Belfast itself was represented as four equal demand nodes. Static head from the SRs was used to provide system pressure in the city.

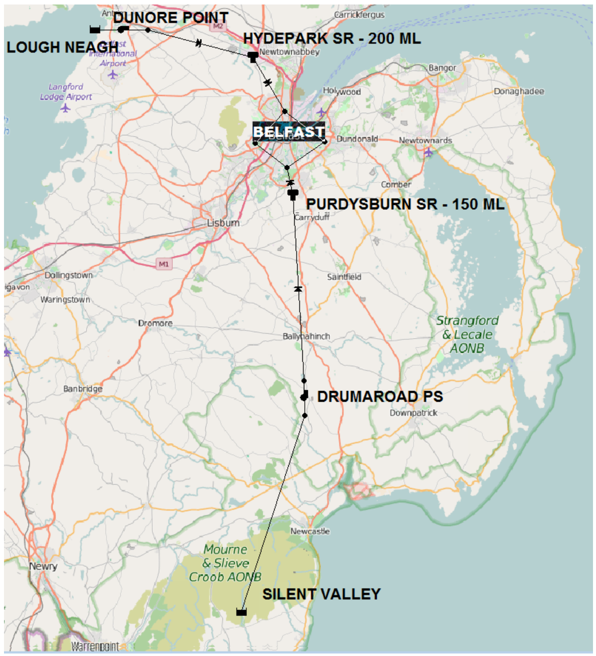

Figure 4: *Simplified representation of Belfast water supply (EPANET)*

Table 1: Belfast's main sources of water [18] [19]

	Mourne Conduit	**Lough Neagh**
Pipe length	56 km	18 km
Service reservoir capacity (approx.*)	150 Ml	200 Ml
Total head gain	-76 m	90 m
Max pumped flow	130 Ml/day	180 Ml/day
Pump power*	1.2 MW	3 MW

**Approximated from available data*

4.3. Scenarios

For both models, four scenarios were considered:

- **Minimise consumption** - Minimising energy consumption and calculating cost on the basis of final EP2 price (base case).

- **EP2** - Minimising cost on the basis of the final EP2 price.
- **EA1** - Minimising cost on the basis of EA1 forecast price and calculating cost on the basis of final EP2 price.
- **Maximise wind** - Maximise wind power utilisation by aligning demand as much as possible with periods of high wind penetration.

4.4. *Optimisation Method*

Both systems were optimised on a daily basis in the period 1 April 2012 - 31 March 2015. Real data for EA1 and EP2 SMP were used as inputs, as were data for wind generation and penetration. Water demand profiles were taken from data supplied by NIW for previous work [33], and scaled according to the size of the system. A GA was used for the main optimisation, which integrated with the EPANET hydraulic solver to assess the viability of potential solutions. Candidate solutions were 72-bit binary strings in the case of the 'Van Zyl' model and 48-bit strings in the Belfast model, corresponding to the operation of each pump modelled hourly over a 24-hour period. Hydraulically infeasible solutions were penalised, and feasible solutions scored based on the objective function of the scenario modelled. A solution was produced for each day in the modelled period, with the outputs at the end of each day used as the initial conditions of the following day.

In the 'Van Zyl' model, 150 generations of GA were used, while 50 were used in the Belfast model. Both used a population of 200. The crossover rate was 100%, meaning all solutions were 'interbred'. The mutation rate was 3%. These figures were arrived at through empirical evaluation. A flowchart of the methodology can be seen in Fig. 5.

4.5. *Objective Function*

For each scenario, the optimisation objective function was different. In the EA1 and EP2 scenarios, the objective was minimisation of cost (Eq. 1).

$$\text{minimise:} \quad \textstyle\sum_{i=1}^{24} E_i \tag{1}$$

In the 'minimise consumption' scenario, it was to minimise the overall quantity of energy consumed (Eq. 2).

$$\text{minimise:} \quad \textstyle\sum_{i=1}^{24} P_{p,i} \quad \forall p \tag{2}$$

The objective of the 'max wind' scenario was to maximise the quantity of wind energy consumed (Eq. 3).

$$\text{maximise:} \quad \textstyle\sum_{i=1}^{24} W_i \tag{3}$$

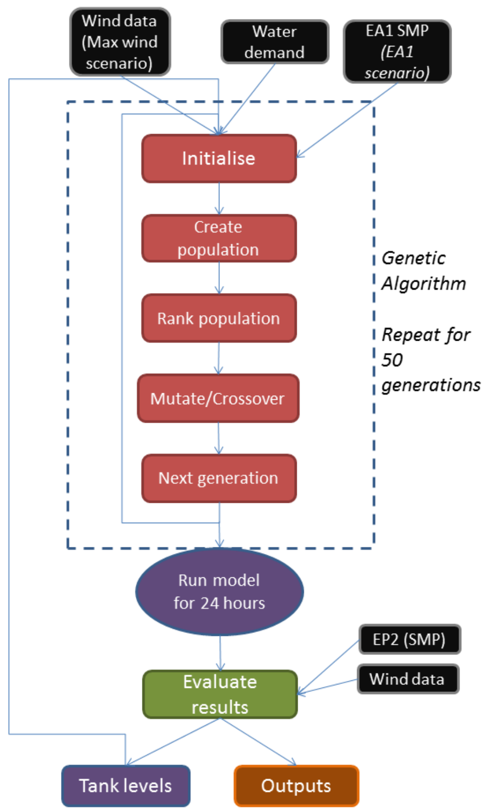

Figure 5: *Genetic Algorithm and model methodology*

4.6. *Constraints*

For both service reservoirs, the reservoir level at time period i was equal to the reservoir level at time period $i-1$ minus the outflow during $i-1$ plus the inflow during $i-1$.

$$R_{p,i} = R_{p,i-1} - D_{p,i-1} + F_{p,i-1} \quad \forall p\ \forall i \tag{4}$$

The cost of electricity consumption during time period i was equal to the unit cost of electricity during i multiplied by the power consumption of the pumps during the same period.

$$E_i = M_i P_{p,i} \quad \forall p\ \forall i \tag{5}$$

SR levels were allowed to vary between specified minimum and maximum levels (Eq. 6).

$$R_{p,min} \leq R_{p,i} \leq R_{p,max} \quad \forall p\ \forall i \tag{6}$$

4.7. *Belfast Model Constraints*

There were two constraints implemented in the Belfast model that were not in the 'Van Zyl' model -

abstraction from Silent Valley Reservoir was limited to 130 Ml per day, and a 'mass balance' constraint was enforced, requiring SR water levels to be at least 90% of initial level (on 1 April 2012) at the end of each day (see Eq. 7). The 'mass balance' constraint was necessary to prevent reservoirs having insufficient capacity for high-demand days.

$$\begin{aligned} &\textstyle\sum_{i=1}^{24} F_m \leq 130 \times 10^6 \\ &R_{p,i=24} \geq 0.9 R_{p,initial} \qquad \forall p \end{aligned} \tag{7}$$

4.8. Hydraulic Modelling

The Hazen-Williams equation (Eq. 8), [34] is an empirical formula which models the pressure drop of water flowing in pipes. The EPANET solver uses this equation to calculate system pressure losses, allowing accurate calculation of F and D at each time step. Pipes were modelled as plastic-lined, with a roughness coefficient (C) of 130.

$$\frac{h_f}{L} = \frac{10.67 Q^{1.85}}{C^{1.85} d^{4.87}} \tag{8}$$

5. Results

The algorithm output data for each day showing reservoir level variation, pump operation, flow rates, energy consumption and final solution feasibility (a feasible solution was found for all days with both models). Table 2 provides a summary of the salient data.

5.1. 'Van Zyl' Model

Despite serving the same demand, the scenarios modelled showed a significant variation in the total amount of water pumped. This is because pump 3B (see Fig. 3) acted as a top-up pump, transferring water from one SR to another. The 'max wind' scenario saw this pump used extensively, thus resulting in the higher energy consumption and pumped flow averages that can be seen in Table 2.

The 'minimise consumption' scenario consumed 2% less electricity then any other scenario while also maintaining the lowest average value of pumped flow. Despite this, it was the most expensive scenario, costing 13.4% more than the EP2-based optimisation (Fig. 6).

All scenarios showed an increase of wind power contribution compared to the system average (Fig. 7). Optimising on the basis of the wind penetration saw a large increase of wind contribution - 18.2% higher than what would be expected from the system average.

EA1 forecast price was consistently lower than the final EP2 price (underestimating final cost by 13.6% on average) but was still cheaper than two of the three other scenarios. This optimisation also showed similar contributions from wind power to the EP2 case.

5.2. Belfast Model

All four scenarios of the Belfast model showed very similar values for total pumped flow, as would be expected from the radial nature of this network. Energy consumption and pumped flow do not correlate directly due to the different energy consumptions of both supplies, and the fact that the relationship between flow rate and power depend on the operating head of the system, which vary due to the level in the SRs. The 'max wind' scenario, which paid no heed to the cost or quantity of energy, gave the highest values for pumped flow and power consumption but also saw a 19.7% increase in wind contribution compared to the system average (Fig. 9) while also being 10.4% cheaper than the 'minimise consumption' scenario.

A similar pattern of operating cost was evident for the Belfast model as for the 'Van Zyl' model: EP2 optimisation was the cheapest, followed by EA1. The one exception to this was the 'minimise consumption' scenario - this actually produced higher power consumption than either the EA1 or EP2 optimisations. This is due to a cycle observed in the output data, caused by the 24-hour horizon of the optimisation - initially, both service reservoirs would be allowed to drain as much as possible in order to minimise pumping. As the optimisation started again for the following day, both reservoirs would be depleted and significant pumping would be required to maintain water supply. The Lough Neagh supply consumed approximately 2.5 times more energy for each litre of water pumped compared to the Mourne supply. In the price- and wind-based scenarios, more use was made of the cheaper Mourne supply, thus reducing the need for the more expensive Lough Neagh water. In the Belfast model, 'max wind', was cheaper than 'minimise consumption' (Fig. 8). This may have been due to the fact that the 'Van Zyl' 'max wind' scenario consumed significantly more power than the other scenarios (thus increasing energy cost) while the Belfast 'max wind' scenario consumed only slightly more.

EA1 optimisation underestimated the final EP2 cost by 13.8% on average but saw an increase in wind power contribution of 7.8%.

On average, across all scenarios, the Lough Neagh supply provided 51% more water than the Mourne supply, due to the constraint on abstraction from Silent Valley and the larger volume of the Hydepark SR. 0.16 kWh were used by the Mourne supply pumps for each

Table 2: Summary of Results, April 2012 - March 2015

Daily Averages	**Min. Cons.**	**EA1**	**EP2**	**Max. Wind**
'VAN ZYL' MODEL				
Energy consumption (kWh)	3628	3705	3713	3885
Final (EP2) cost (£)	189.6	173.8	164.2	183.1
EP2 unit cost (p/kWh)	4.79	4.69	4.42	4.71
Pumped flow (m^3)	14885	15359	15613	16229
Cost per m^3 pumped (p)	1.274	1.131	1.052	1.128
Expected wind contribution (kWh) *(18.65% system av. penetration)*	676.6	690.8	692.4	724.4
Wind contribution (kWh)	689.8 (+1.95%)	732.7 (+6.06%)	745.9 (+ 7.73%)	856 (+18.17%)
BELFAST MODEL				
Energy consumption (kWh)	55250	55071	55045	55874
Final (EP2) cost (£)	2846	2425	2278	2550
EP2 unit cost (p/kWh)	5.15	4.40	4.14	4.56
Pumped flow (m^3)	180449	180873	180903	185957
Cost per m^3 pumped (p)	1.577	1.341	1.259	1.371
Expected wind contribution (kWh) *(18.65% system av. penetration)*	10303	10270	10265	10419
Wind contribution (kWh)	10473 (+1.65%)	11066 (+7.75%)	11352 (+ 10.60%)	12467 (+19.65%)

m^3 of water supplied, while the Lough Neagh pumps consumed 0.4 kWh for each m^3 pumped. This was consistent across all scenarios and is due to the fact that the Lough Neagh pumps had to pump against a head of 90 m, while the Mourne pumps were moving water against a negative head (-76 m).

6. Discussion

In this research, two water supply systems (the 'Van Zyl' test system and a model representing the supply for the city of Belfast) were optimised on the basis of minimising electricity consumption, maximising wind power contribution, and minimising electricity cost (using both forecast and actual system price). Pumping costs and contribution from wind power were quantified, with the Belfast model giving results consistent with the benchmark system.

EP2 optimisation was consistently the least expensive, as might be expected as EP2 represents the final cost of wholesale electricity. It would not be possible to optimise on the basis of EP2 in reality as it is not known until four days after the event, but it represents the most cost-efficient operation possible. EA1 optimisation is achievable, as EA1 data are made available one day in advance. Despite underestimating final costs by approximately 14%, EA1-based optimisation nonetheless represented a significant saving compared to the non-price-based scenarios. A water utility optimising pumping on the basis of the publicly available SMP forecast could make significant savings compared to normal operation.

It should be noted that all prices discussed here are wholesale prices - they do not reflect the final price a customer would pay as SMP does not include the cost of distribution or transmission. It can be reasonably assumed that this added cost would be fairly constant [35] and would not affect the results seen here, other than to increase the cost of all scenarios by a comparable margin. A further limitation is that neither of the models analysed here included constraints relating to water treatment, which is either a continuous or batch process. Water is treated before being pumped to service reservoirs, with the treatment plant usually being on the same site as the pumping station (as is the case with both Dunore Point and Drumaroad). The Belfast model represents a simplification of the reality, in that the city itself was modelled as four demand nodes and offtake from both conduits for other areas were ignored; however, this should not have a significant effect on the results as the demand was scaled to compensate for the excess water that would have otherwise served areas beyond Belfast, and flow within the Belfast network

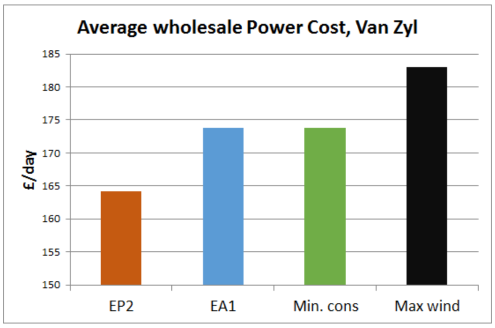

Figure 6: *Average SMP energy cost, 'Van Zyl' model*

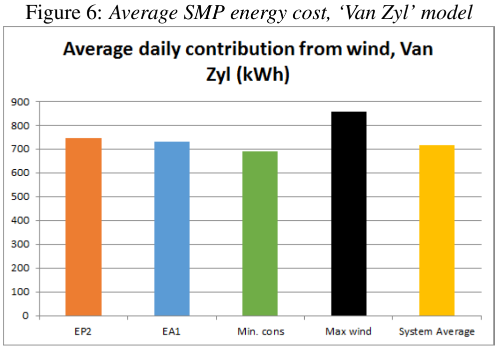

Figure 7: *Average contribution of energy consumption from wind, 'Van Zyl' model*

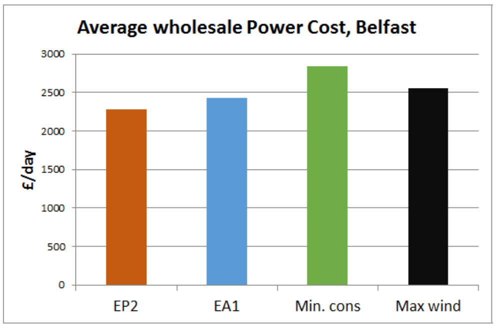

Figure 8: *Average SMP energy cost, Belfast model*

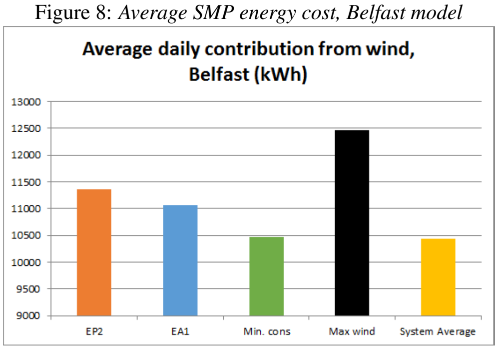

Figure 9: *Average contribution of energy consumption from wind, Belfast model*

itself would have little bearing on the demand from the SRs.

For both models, the 'max wind' scenario showed a significant cost saving compared to the 'minimise consumption' scenario. Both SMP-based optimisations also showed significant increases in wind power contribution compared to both the system average and the 'minimise consumption' scenario. This reinforces the suggestion that there is a correlation between wind penetration and system price. While not as conducive to high wind contributions as wind-based optimisation, SMP-based optimisation represents a viable means of incentivising demand to react to wind generation. However, the difference in wind contribution between the EA1 and EP2 scenarios shows that this link is dependent on the accuracy of wind forecasting in the operation of the electricity market. The very high increases in wind contribution seen in the 'maximise wind' scenario are also unlikely to be achievable in reality as they are based on perfect foresight of wind generation.

In the Irish SEM, the EA1 forecast is updated later on D-1 with an EA2 forecast, and then again on the morning of the day itself with the WD1 forecast. In practice, an EA1-based pumping schedule could be updated when these forecasts are released. The increased accuracy of these forecasts should correlate with costs and wind contributions closer to those seen in the EP2 scenario. High-wind events are frequently multi-day, and so if a period of sustained high wind was forecast, relaxing the mass balance constraint of the Belfast system could allow tanks to be filled during this period of low cost generation, or allow the water level to gradually deplete in anticipation of such an event.

7. Conclusion

The main contribution of this study is in showing that price-based optimisation of water supply provides an opportunity to benefit both the water utility (through reduced cost) and the power system (through increased uptake of wind power). Providing that the consumer is paying a tariff based on the wholesale cost of energy, optimising pump operation on the basis of an SMP forecast would allow the water utility to make significant cost savings compared to normal operation while increasing utilisation of wind generation. In a market such as the Irish SEM, where wind power is price-taking rather than price-making, optimising on the basis of SMP effectively amounts to market-driven DSM (rather than that which involves explicit operator control) which has the advantage of encouraging alignment of energy consumption with wind generation. Optimising on the basis of the wind penetration itself increases the contribution of wind generation even further, while still reducing the cost of electricity. Implementing this in reality would be a more explicit form of DSM, either by direct signal from the energy utility or by designing a tariff based entirely on wind generation rather than SMP.

Both approaches provide advantages for both consumer and system, but a trade-off is required between cost and wind power uptake. If the system operator wished to maximise wind generation to the fullest extent, more explicit DSM would be desirable, thus providing the benefit seen in the 'max. wind' scenario here. However, if flattening of the load curve was also a priority for the system then SMP-based optimisation would be advantageous in that it would discourage load during peak times (which, due to variable generation, do not always occur at the times reflected by standard multi-rate tariffs) while also, to a certain extent, promoting utilisation of wind power.

The methodology used here could be applied to any water supply system, with modifications to suit the needs of the particular system - for example, to take account of water treatment constraints, or daily or seasonal limits on water abstraction. The effectiveness of the method would in large part be dictated by the flow rate of the pumps and storage capacity of service reservoirs in relation to the water demand. It should also be noted that the approach detailed here could be applied to any dispatchable load. If implemented on a sufficient scale, it would reduce both the need for thermal generation and for wind power curtailment.

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