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Energy saving through modifications of the parallel pump schedule at a pumping station: A case study

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ABSTRACT

Diverse state-of-the-art methods can be utilized to reduce energy consumption in water supply and distribution systems, including using high-efficiency equipment, shifting energy use away from peak demand times, energy recovery and storage devices, and renewable energy. However, the benefit of using high efficiency equipment can sometimes never be completely realized, as the performance of the individual pumps within a site can be reduced from optimal owing to a variety of reasons: a lower operating rate of the water treatment plant than the design flow rate, hydraulic conditions such as pipeline resistance or determined pressure, and pump scheduling. This research focused on optimizing pump scheduling through real-time monitoring utilizing smart temperature and pressure sensors, wireless low-power data communicators, and a pump data analysis algorithm to determine the hydraulic efficiency from thermodynamic state variables with subsequent parallel pump optimization. Thermodynamic pump performance measurements provided real-time information, including flow rate, specific power, and pump efficiency, in both individual and parallel pump operations. Evaluation of the specific power under diverse parallel pump operation scenarios demonstrated a variation of 0.115–0.140 kWh/m^3 in the range of 7800–10,100 m^3/h. However, the deviation in specific power was more than 17 % when operating at less than 7800 m^3/h and more than 10,000 m^3/h. The summary of the pump combination operation suggested that energy could be saved by up to 15 % by optimum pump scheduling, that is, small capital investment, simple optimization of control through thermodynamic state variable measurement, analysis, and feedback.

1. Introduction

Recently, the portfolio of water treatment and supply businesses has focused on improving and replacing aging water infrastructure, optimizing operation and management, and reducing power consumption [1–10]. Diverse quantitative and qualitative sensors are installed in a water supply system to provide real-time information to help optimize water purification process operations and save energy. Quantitative measuring instruments are representative of flow, pressure, water level, and electricity meters, and are utilized to control the retention time of the reaction tank, feed load into each reactor, pump operation and management, etc. [11–12]. Qualitative sensors are used for pH meters, water temperature meters, turbidity meters, particle counters, chlorine concentration meters, etc., which are predominantly utilized for chemical injection control and treatment performance management [13–17]. Real-time sensing data is also typically used to determine the current operational conditions and to diagnosis the management status [18–20]. In other cases, real-time acquired data are sometimes utilized as input in algorithms to evaluate the performance of the unit process or the efficiency of the machine applied at the water treatment plant. Finally, real-time sensors are used to reduce the chemical dose and energy consumption, or to achieve process optimization by building a model through statistical analysis or data deep learning [21–23]. However, although real-time sensing data, deep learning, and modeling have been limitedly utilized for research purposes, they are rarely used for real full-scale operation with long-term validation. This is because waterworks operators still want to operate and maintain it based on their knowledge and experience rather than on deep learning and modeling data. The developed model still needs time to secure reliability in the field in the long run and for its verification by reflecting diverse field

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characteristics. Big data studies and cases primarily focus on optimizing water treatment processes rather than saving energy for power consumers in water [24–27]. However, efforts towards pump scheduling using generic algorithms have been initiated to minimize the water distribution system pump operation cost and storage capacity [28].

The number of pumps in a pumping station depends on its design capacity, flow rate variability, and the type of pumps deployed. The major concern is to reduce the electricity costs of the pumps under operational conditions [29]. Motor-driven pumps account for approximately 20 % of the total electricity cost and have a significant impact on the unit cost of tap water production in water purification plants [30–32]. Pumps are often operated outside of design conditions due to network (system curve) characterization errors in the design process, changes in water demand patterns, reservoir water level management, reservoir inlet valve regulation, and pipeline pressure management.

Over time, the hydraulic characteristics of pumps change due to usage. Internal friction increases the roughness of wetted surface, and primary recirculation leads to expansions of wear ring or wear plate clearances. Consequently, the output and efficiency of the pump decreases within a given system. This is one reason why pumps are often oversized, such as having a larger diameter impeller than required for a given duty. Additionally, there is a tendency to specify the best efficiency point (BEP) at the maximum output of plant rather than the average, and conservative design estimates of system properties further contribute to pumps operating at a lower head, higher flow, and reduced efficiency beyond the BEP. Common measures to compensate for reduced efficiency include throttling the pump discharge valve to return the pump to the BEP or reducing the impeller diameter. However, operating pumps under such conditions shortens their lifetime and increases energy consumption [33–34]. While throttling can increase pump efficiency, it also leads to increases head-specific cost.

During operation, the fluid in the pump experiences pressure and resistance, resulting in a decrease in pump discharge volume over time. This fluid resistance causes the pump to be overdesigned. In the pump design stage, the operating point is determined based on the total head and desired flow rate, and then the specifications and number of pumps are selected. Furthermore, when considering the peak flow rate and maximum total head in pump selection, the pump system may have a significant margin of total head compared to the actual head. This allows for an overestimated flow during actual pump operation, often leading to the bridging of the discharge valve or cutting of the impeller to adjust the excess flow rate. Operating the pump at such an unbalanced flow rate and total head shortens the lifetime of pumps and valves, and increases energy consumption [35–36].

Hydraulic measurement methods are simple as existing measurement sensors, such as individual pump pressure and total flow meters, are available, and existing operation conditions and pipe changes are unnecessary. However, it is very difficult to install a flowmeter on an individual pump by securing the pipe length in a straight section for accurate efficiency computation [37]. In the case of a pump station with a large water supply, it is impossible to operate one pump alone; therefore, it is essential to combine several pumps and measure the flow rate of each pump, but it is difficult to diagnose the efficiency of individual pumps [38–40]. Therefore, research has been conducted on data utilization, sensor application, and optimal model development to optimize the operation of existing running pumps after selecting pumps for the site [41–46].

Wu et al. [47] developed an optimization model based on the genetic algorithm (GA) to optimize the rotation speed and valve position of the pump and reported that it improved the efficiency of a single pump but was degraded when applied to parallel pump systems. Kim et al. [48] introduced sensing technology and thermodynamic efficiency measurement methods to measure the efficiencies of individual pumps. Based on this, a proper combination of pumps was selected, and the minimum unit power consumption was derived utilizing a curve of least-squares approximation and subsequently tested in the field. Hyung [49] used a genetic algorithm to develop an optimal pump operation method that considers stable water quantity and safe water quality. Shin et al. [50] attempted to reduce electricity costs by increasing the volume of water transmission and supply during the off-peak load. They developed a scheduling program for water intake pumps with water supply flow rate, and simulated the energy savings with the developed program. As a result, it was verified that the annual water intake power cost could be reduced by 5.1 % and 106,780 USD, including the water supply power cost by 5.5 % and 100,674 USD, compared to the case of equal usage of the pump regardless of the electric rate schedule. Sarmas et al. [51] used machine learning models to forecast the electricity consumed and produced by renewable energy sources on an hourly basis. Their forecasts optimally allocated the operating hours of the pumps to minimize the predicted peaks. Smart scheduling of water pumps could reduce the daily and weekly deviations in electricity consumption by more than 15 %.

According to previous studies, it is essential to monitor the actual operation efficiency of pumps operating outside design conditions and to determine the economical pump combination for meeting water demand. Therefore, this study utilized a thermodynamic method with a real-time sensitive temperature sensor to estimate the actual operating efficiency of individual pumps at a pump station where individual pump performance could not be measured with the existing meters. Based on these estimations, the specific power was calculated under diverse pump combination conditions, and the economic savings effect of pump scheduling for the desired flow rate was evaluated. The practical long-term tests and verifications could serve as a catalyst for lowering the burden on waterworks staff to embrace digital water technologies in the field such as smart sensors, data collection and processing, and an artificial intelligence algorithm.

2. Materials and methods

2.1. The case study context: a pump station

This study was conducted at a water supply pump station to deliver purified water to a reservoir. The test site was located in a water purification plant in Seo-gu, Incheon City, Korea, as depicted in Fig. 1. The water resource is the surface water from the Han River pumped to the G water treatment plant (WTP) through two pumping stations with a transmission pipeline of 2000 mm diameter. The treatment process for the G WTP comprised rapid sand filtration and a granular activated carbon adsorption process (GAC), as summarized in Table 1. The water supply pump station was designed to supply the chlorinated water after GAC to 14 reservoirs with a 413,000 m^3/day capacity, as described in Fig. 2. The G WTP operation rate was 62.8 %, which was lower than that of the original design, causing a change in the operation point of the pump performance.

A single-stage horizontal centrifugal type was applied for pumps in the water supply pump station. The detailed specifications of the pumps are represented in Table 2. Pumps 1 through 5 were the main pumps, and pumps 6 and 7 were auxiliary function pumps. To cope with changes in the pump flow rate and real head by year, pumps 4 and 5 were designed to control the pump speed via variable fluid couplings, and the remaining pumps were fixed-speed pumps. The existing parallel pump operation approach was combined with one main fixed-speed and one variable-speed pump to satisfy the water demand, and an auxiliary fixed-speed pump was included to the combination to satisfy the increased water demand. The rpm of the variable-speed pump is controlled, based on the need of adjustment of the water level of the reservoir or the pressure of the supply pipeline.

G WTP covered the water supply service areas, serving a total of 748,777 customers, with the help of two boosting stations and 14 service reservoirs (excluding one GD tank under the construction plan), as shown in Fig. 3. The service reservoirs were designed to store up to 12 h' worth of water supply per day to accommodate fluctuations in water

Fig. 1. The test bed location.

Table 1
Unit process specifications of G WTP.

Unit process	Size and specifications
Equalization (#1, 2), L × W × H(m)	17 × 42 × 5.3, 2 basins
Mixing (#1, 2,)	Flash mixer
Coagulation (#1), L × W × H(m)	15 × 15 × 3.8, 8 basins
Coagulation (#2), L × W × H(m)	13.5 × 13.5 × 3.5, 6 basins
Sedimentation (#1), L × W × H(m)	15.5 × 67 × 4.5, 6 basins
Sedimentation (#2), L × W × H(m)	14.1 × 68 × 4.8, 6 basins
Sand filtration (#1, 2), L × W × H(m)	Single media, 8 × 16, 16 basins
GAC[a] (#1, 2)	EBCT[b] 15.2 min, LV[c] 10.7 m/h

[a] Granular activated carbon adsorption.
[b] Empty bed contact time.
[c] Linear velocity.

demand. The water supply pumps at the WTP were scheduled to maintain the appropriate water level in each service reservoir and control the variable flow pump speed to ensure the proper pressure in the water supply pipes.

2.2. Methods of sensor installation on the working pumps

G WTP manages the total water supply via installation of electric flow meters in the integrated pipes of seven water supply pumps. The purpose of this study was to evaluate the performance of individual pumps and establish a suitable pump combination to supply the final water to the target reservoirs. For real-time pump performance monitoring, the FREEFLOW system (FFI3 System, Riventa Ltd.) was installed in the water supply pump building. This pump station building had a narrow footprint, wherein flow meters could not be installed to measure each pump flow rate. Therefore, thermodynamic pump monitoring instruments were considered to install on the existing pump apparatus within a limited space. The instruments were smart temperature sensors (TT4-300-10, Riventa Ltd.), pressure sensors (PT4-010-2, PT4-020-2, Riventa Ltd.), and Internet of Things (IoT) wireless mesh network hubs with local screens. This system provided precision measurements

Fig. 2. The water supply pump station used as test bed.

Table 2
Specifications of water supply pumps used in the test bed (OEM[d] data).

Name	Power (kW)	Flow rate (m^3/min)	Head (m)	Speed (rpm)
1MF[a]	825	69.5	43	707
2MF	825	69.5	43	707
3MF	825	69.5	43	707
4MV[b]	675	69.5	43	710
5MV	675	69.5	43	700
6AF[c]	425	34.8	43	1188
7AF	425	34.8	43	1188

[a] Main pump with a fixed flow rate.
[b] Main pump with a variable flow rate.
[c] Auxiliary pump with a fixed flow rate.
[d] Original equipment manufacturer.

with measurement transducers installed in the suction point (inlet) and delivery point (outlet) of each pump, as depicted in Fig. 4. The temperature sensor had differential temperature accuracy of ±0.0010 °C and differential temperature resolution of 0.0001 °C within operating temperature range of 0 to 40 °C. Additionally, ISO/IEC 17025 was used by temperature sensors for calibration. The pressure sensor had measurement range of 1–20 kg_f/cm^2 and pressure measurement accuracy of ±0.1 %. Smart sensors equipped with IoT technology were designed for automatic recovery functions and energy savings used for communication.

2.3. Engineering dashboard of human machine interface

The engineering dashboard was designed to monitor pumps operation status in real time, extract from the operation data and visualize pump performance. Fig. 5 shows the customized engineering dashboard of human machine interface (HMI) for test bed. On the HMI left screen, information on parallel pump scheduling and real-time performance of the current pump combination is provided. Additionally, the performance of the individual pump is also provided to the system users, including the head, electric power, pump efficiency, and flow rate of each pump. A real-time pump system curve is provided on the HMI right screen based on a thermodynamic pump-efficiency computation algorithm. It depicts the total differential head and specific power according to the flow rate supplied through the parallel pumps. Additionally, the operation point under the current pump combination is marked by a red dot in the accumulated system curves. This allows system users to establish the optimal pump combination in the future according to the current parallel pump performance.

3. Theory

Thermodynamic tests of pumps require the use of the testing standard BS EN ISO 5198:1999, which deals with performance tests of centrifugal, mixed flow, and axial pumps and specifies the code for hydraulic performance tests and precision class (BSI EN ISO, 1999). For this method, the required measurement parameters include suction and discharge pressure (Pa), suction and discharge temperature (°C), electrical input power (kW), computing in mass flow rate (kg/s), volume flow rate (m^3/h), drive efficiency (%), pump head (m), and pump efficiency (%). The diagram of the thermodynamic measurement system was shown in Fig. 6. The thermometric technique uses an enthalpy-

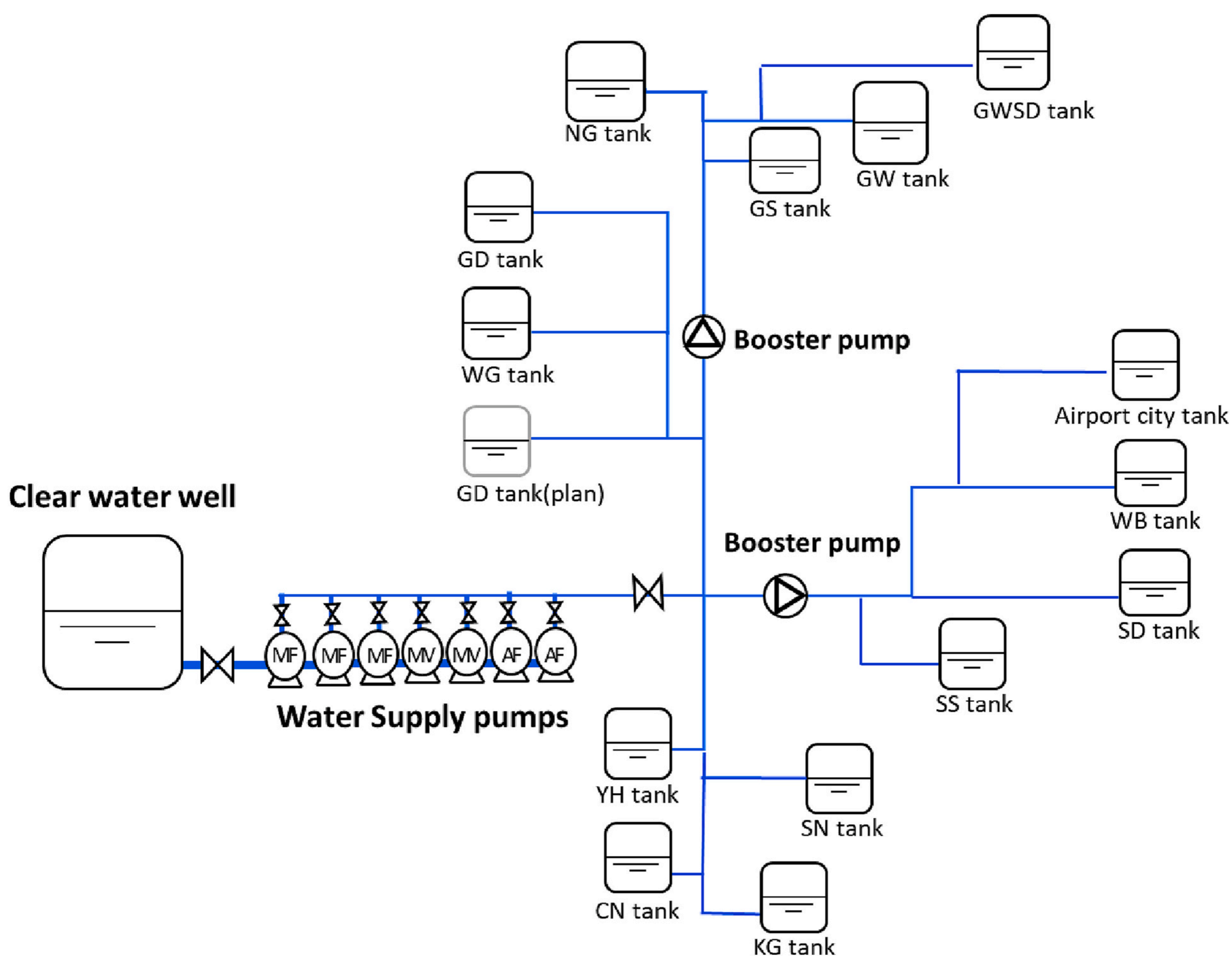


Fig. 3. Schematic diagram of the water supply system from the pump station to service reservoirs.

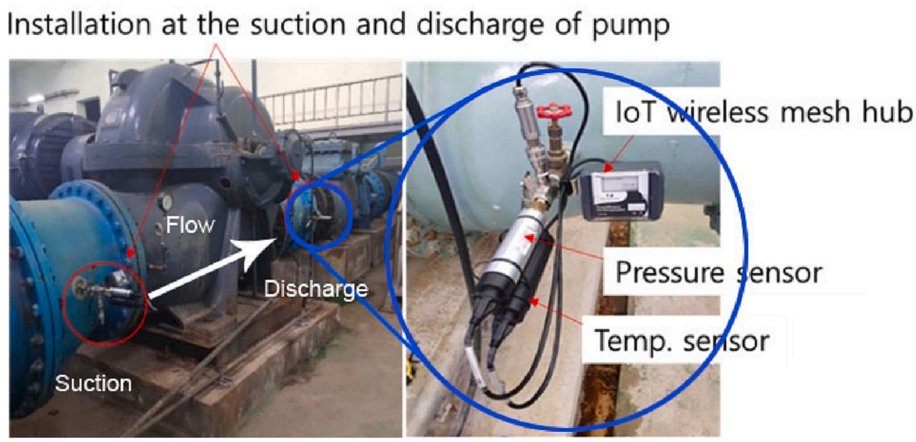


Fig. 4. Sensors and IoT modules installed at the suction and delivery of pumps.

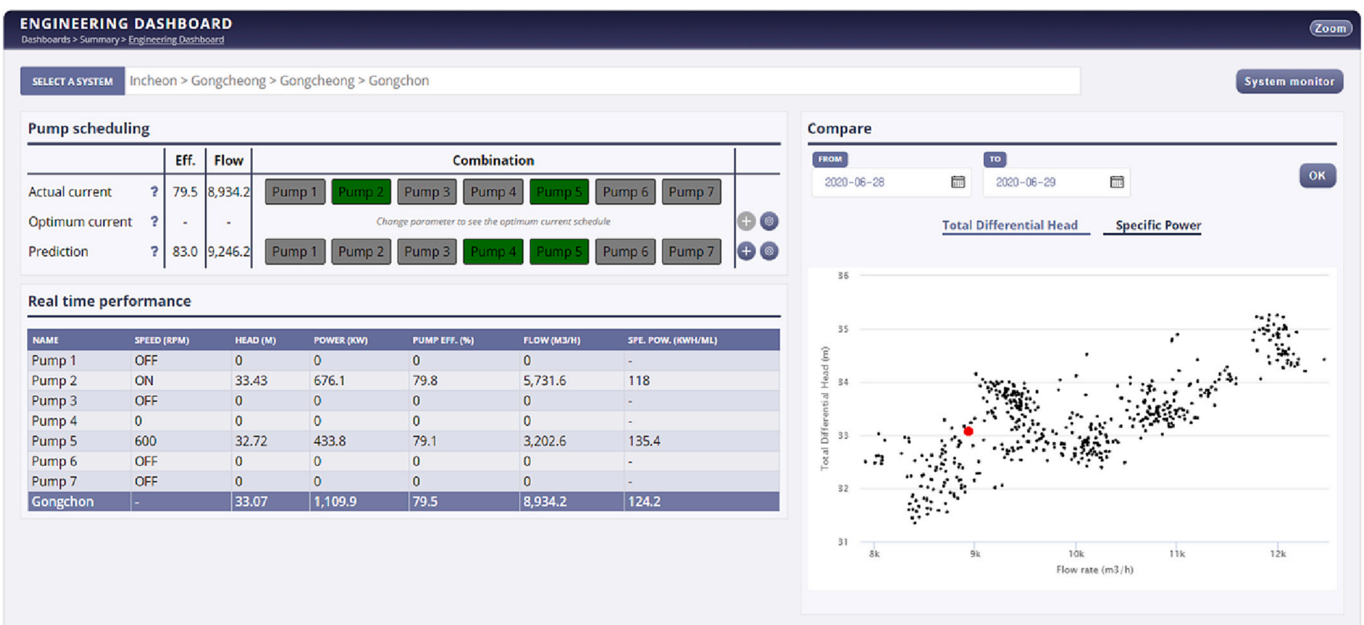


Fig. 5. Engineering dashboard for human machine interface module.

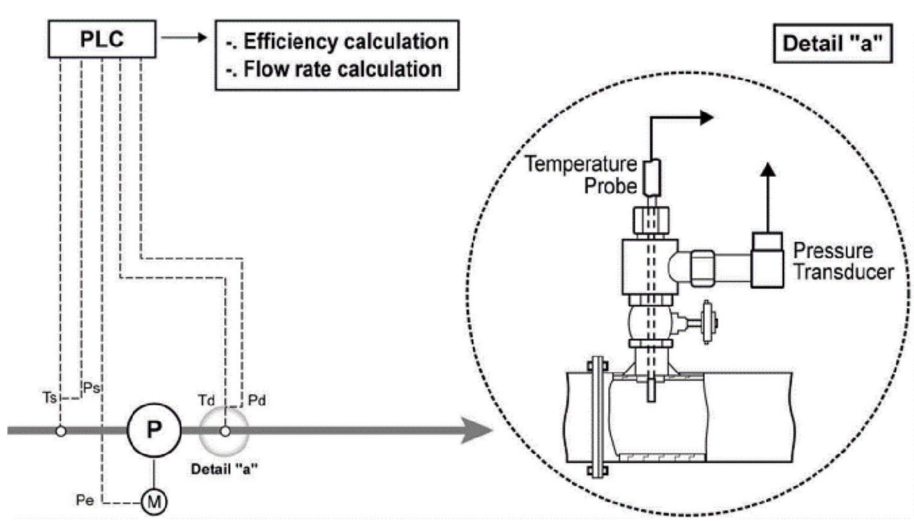


Fig. 6. Diagram of thermodynamic measurement system.

entropy mapping method to determine pump efficiency without the flow rate measurement. Therefore, temperature and pressure before and after the pump are measured. Both transducers are inserted through one ½" BSP tapping. The pressure transducer connects through a hydraulic quick release coupling in the side port and the temperature transducer through a resealable compression gland. The temperature probe is inserted 50 mm into the pipework at which time the gate valve is gently tightened onto the probe shaft adding a second point of contact to limit vibration due to the passing fluid. The pressure data of suction and delivery of pump was used to calculate the static pressure in the pump pipeline. The thermodynamic method is comparatively low cost for site use purchase and site installation. It has simple installation requirements and is not dependent on straight lengths of pipe to affect an accurate measurement. In addition, it is well suited to on-site application, generally for more than 15 m of head.

The pump efficiency was computed using only temperature and pressure measurements. The flow was then derived from other parameters. The flow measurement uncertainty is a product of all others, and the pump efficiency provides the greatest bearing. In both the thermodynamic and conventional methods, the hydraulic work was used in Eq. (1).

$$P_e \cdot \eta_m \cdot \eta_p = \dot{m} \cdot g \cdot \Delta H = \overline{\rho} \cdot g \cdot \dot{Q} \cdot \Delta H, \tag{1}$$

where, η_m is the motor efficiency

η_p is the pump efficiency
P_e is the electrical power input (W)
$\dot{m}$ is the mass flow rate (kg/s)
$\overline{\rho}$ is the average density of the working fluid (kg/m^3)
g is gravitational acceleration (m/s^2)
$\dot{Q}$ is the volume flow rate (m^3/s)
ΔH is the head rise across the pump (m)

The shaft power (P_S) applied to the pump was computed via the electrical input power to the motor measured by a three-phase power analyzer connected to data acquisition unit (DAU) (FREEFLOW™ DAU, Riventa Ltd.) and then an estimate for the drive and motor efficiency, η_m, was deduced from the data sheet of original equipment manufacturer and applied to Eq. (2).

$$P_s = P_e \cdot \eta_m \, H \tag{2}$$

In the context of pumps, the pump efficiency is defined by Eq. (3).

$$Efficiency = \frac{Water\ Power}{Shaft\ Power} = \frac{1}{1 + \frac{Losses}{Water\ Power}}, \tag{3}$$

where, the shaft power = water power + losses
the losses $= \rho \cdot C_p \cdot \Delta T \cdot Q$.
the water power $= \rho \cdot g \cdot H \cdot Q$

Eq. (3) can be rewritten as Eq. (4). It depicts that the thermodynamic method of hydraulic efficiency determination can be evaluated through observations of temperature and pressure, rather than flow measurements. Therefore, the pump efficiency was determined directly using immediate thermodynamic measurements of the temperature and pressure of upstream and downstream of the pump by using Eq. (4)

$$\eta_p = \frac{1}{1 + \frac{Cp \cdot \Delta T}{g \cdot \Delta H}}, \tag{4}$$

where Cp is the specific heat capacity (J/kg·K) of the working fluid and ΔT is the temperature rise across the pump (K). All pressure transducers were calibrated according to the transfer standards outlined in ISO17025. The static pressures were measured using digital transducers, each connected to the pipework on either side of the pump. The inner diameters of the suction and discharge pipe, d_1 and d_2, respectively, were measured to provide the essential inputs for computing the dynamic head. The total differential head ΔH was thus computed in accordance with the method outlined in ISO 9906:2012, which is summarized in Eqs. (5) and (6). The first term of Eq. (6) is the potential head and is equivalent to the difference in height between the pressure transducers.

$$\Delta H = Potential\ Head + Hydrostatic\ Head + Velocity\ Head, \tag{5}$$

$$\Delta H = Z_2 - Z_1 + \left[\frac{p_2 - p_1}{\overline{\rho} \cdot g}\right] + \left[\frac{U_2^2 - U_1^2}{2 \cdot g}\right], \tag{6}$$

where the density, $\overline{\rho}$, is accurately known for all pressures and temperatures, and the velocity head term is computed iteratively using the flow rate and inlet and outlet pipe diameters (d_1 and d_2), as depicted in Eq. (7).

$$If, U = \frac{4 \cdot Q}{\pi \cdot d^2} \Rightarrow Velocity\ Head = \frac{16 \cdot Q^2}{\pi \cdot 2 \cdot g}\left[\frac{1}{d_2^4} - \frac{1}{d_1^4}\right] \tag{7}$$

4. Results

4.1. Data analysis before setting pump management system

To establish a pump management system in 2020, the existing data on water supply pump operation was evaluated. The operational data of the water supply pump from January to December 2018, before implementing the pump management system, were utilized. Fig. 7 shows the time-series evaluation of the total daily water supplied to all reservoirs. Depending on the reservoir operation conditions, this evaluation revealed a pattern where the average operating flow of water supply ranged between 10,000 and 12,000 m^3/h. There was a decrease in water supply in February and August, while an increase was observed in June, July, September, and November. Throughout the 365-day operating period, the flow rate momentarily dropped to 0 for 5 min due to communication failure, resulting in missing data points when the operating data was collected every 10 s. The annual variation pattern of the water supply was used as the basic data to establish a pump combination scenario for parallel pump operation.

Fig. 8 shows the annual operation status of the water supply pumps that were used to supply purified water to a reservoir before implementing the pump-scheduling system. In large-capacity services that require parallel pump operation, all pumps were continuously in service based on the average pump usage, except for instances of pump failures or piping and valve errors. The main variable-speed pumps (MV) were frequently utilized in the parallel pump combinations, with main pump 5 demonstrating a high operating rate of 28 %. Similarly, main pump 4 was frequently utilized in pump combination scenarios, accounting for 22 % of the annual utilization. As the main pumps with fixed flow rates, pumps 1, 2, and 3 had lower annual utilization rates of 14 %, 11 %, and 0.02 %, respectively. Main pump 3 was rarely used due to a malfunctioning valve in the pump pipe. Among the auxiliary pumps, pump 7 had an annual operating rate of 16 % and was used more frequently compared to pump 6, which had an operating rate of 15 %. Therefore, upon analyzing the annual utilization rates of each pump, it was observed that there were deviations in the utilization rates within the main pump category and the auxiliary pump category. Additionally, a deviation in the operating rate was observed in the main pump responsible for speed control. Consequently, pump scheduling was necessary to achieve balanced pump usage and energy savings.

Fig. 9 describes the annual variation of specific power in relation to the flow rate during the operation of conventional parallel pumps. The specific power range per year for the total flow rate is 0.074 to 0.184 kWh/m^3, indicating a variation of 148 %. Within the flow rate range of 8300 to 12,000 m^3/h, although the average specific power value was optimized, there was a high variation of 142.5 %. This highlights the necessity for optimal pump combination conditions to ensure water

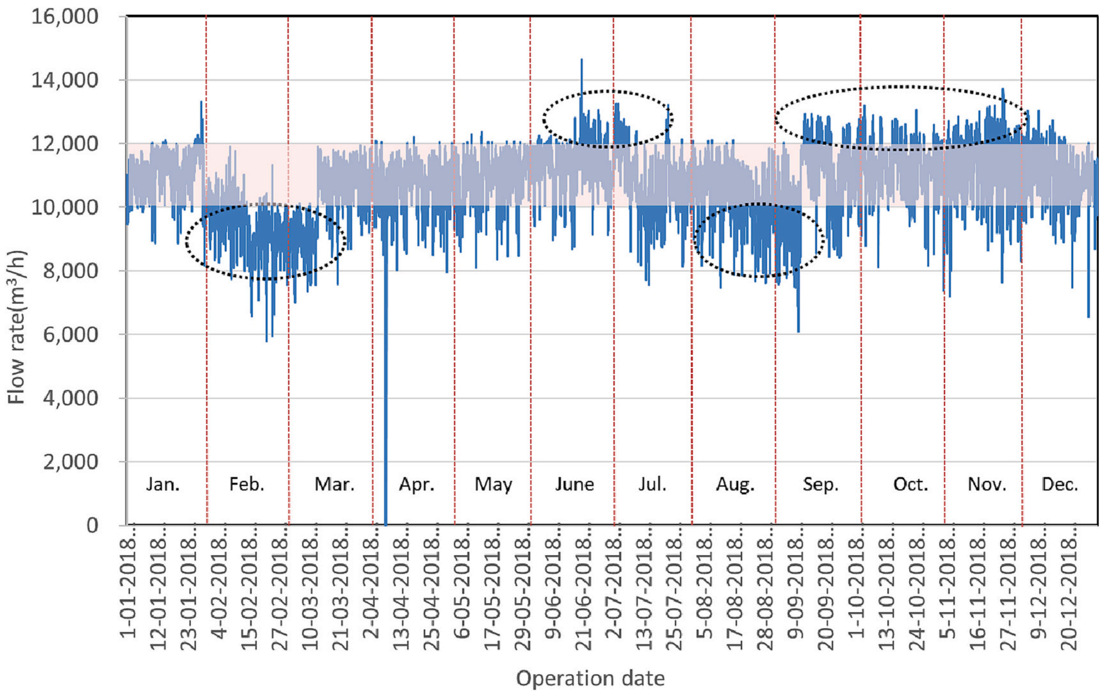


Fig. 7. Time series analysis of annual water supply pattern.

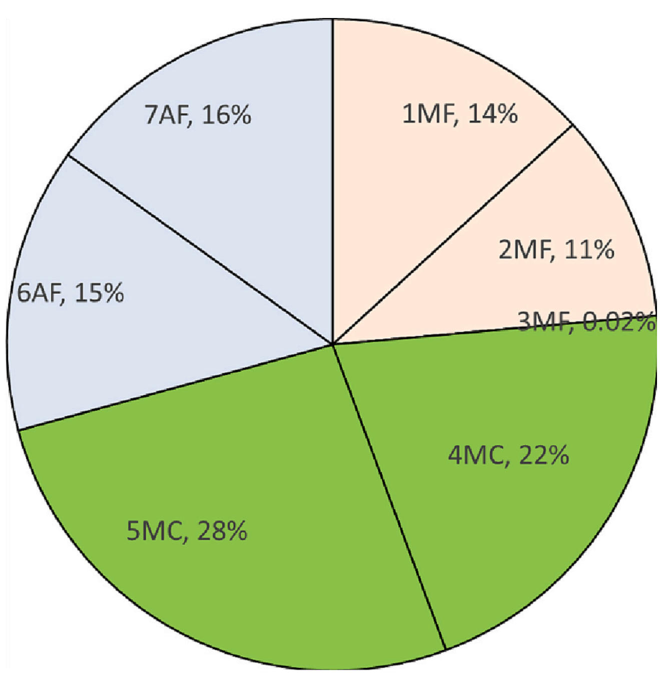


Fig. 8. Annual utilization of individual water supply pumps.

supply economically. Conversely, operating under optimal pump combination conditions with a specific power deviation of less than 11 % was achieved for flow rates below 8300 m^3/h and above 12,000 m^3/h. High specific power was calculated within the average annual supply flow range of 10,000 to 12,000 m^3/h which was a pattern of average water supply flow based on the time series analysis. Therefore, it is imperative to modify the existing pump combination method in the section with high specific power or derive pump combination conditions using high-efficiency pumps.

4.2. Evaluation of differential temperature using sensitive sensors

After installing sensors, data communication/collection devices, and data analysis/diagnostic modules, the short-term operational data were evaluated. Temperature was monitored at the inlet and outlet of the pump through the major sensors in the pump management system. Fig. 10(a) depicts the water temperature difference of the main pump at a constant speed: Pump 1, with a value of 0.025 ± 0.002 °C. Fig. 10(b) depicts the main pump with a variable speed: Pump 4, with a temperature difference of 0.033 ± 0.002 °C. The real-time pump efficiency can be indirectly determined by the temperature difference between the inlet and outlet of each pump. If the temperature difference in the fluid is large, owing to the thermodynamic characteristics, the pump efficiency may be reduced, and the power consumption may be increased.

According to the analysis of the total head according to the flow rate, the head increased with the flow rate, as shown in Fig. 11. The variation in the total head was between 30 and 39 m at the same flow rate. The actual total head obtained from the parallel pump operation was 5–10 m lower than 43 m of initial head of the individual pump (OEM data), as shown in Table 2. Therefore, it was considered that the operation was made on the right of the BEP. Further, it was found that the pumps with an excessive capacity had been selected compared to the desired flow rate. Determining the number of pumps suitable for the flow rates is important in economic terms when there is a large fluctuation in the flow load. The existing pump combination method combines the main variable and fixed-speed pumps with the same capacity and operates or stops an auxiliary fixed-speed pump with a small capacity when the flow rate increases or decreases. As a result, fluctuations in the head were caused by diverse pump combination methods operating at the same flow rate. Above all, there were cases when pumps were operated at a head of 30 m or less. Therefore, it was found that optimal pump combination should be established for low flow rates and low head conditions.

In this study, the total head of the pump was evaluated according to the flow rate. The duty head of the given pump was 43 m, as depicted in Table 2, but the actual operating head of this system was 34.5–36 m, which was 82 % lower than the duty head, as depicted in Fig. 12. Currently, the pump operating point is positioned to the right of the BEP

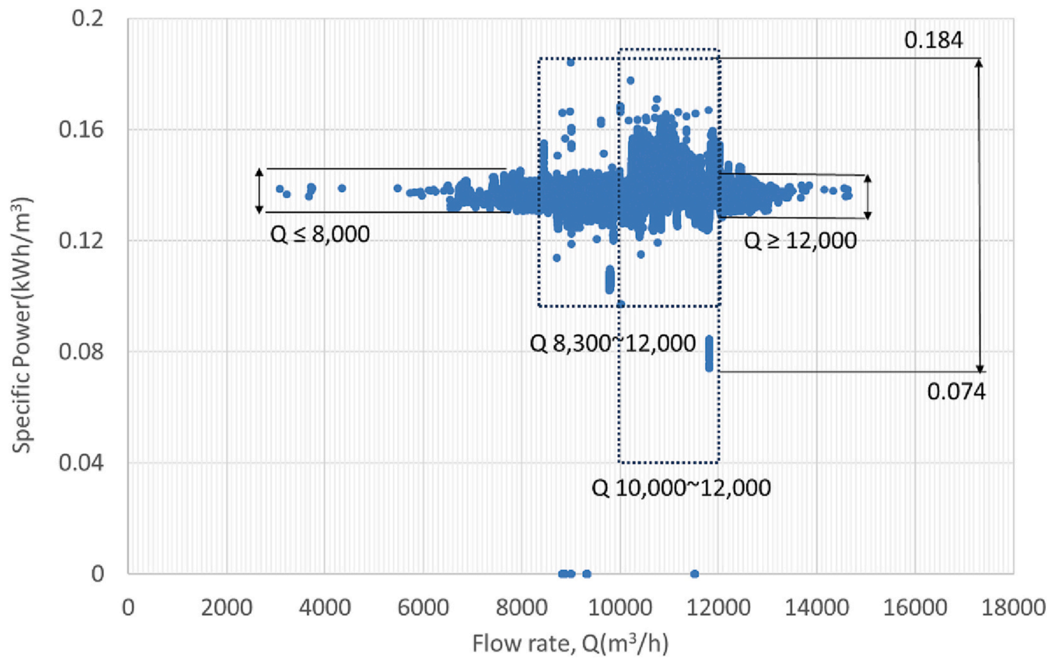


Fig. 9. Characteristics of specific power and flow rate of pumps.

in the performance curve, which may cause low pump efficiency and increase pump wear. In addition, operating beyond the BEP will result in high operational costs.

The specific power via flow rate was monitored in real time and was found to be between 0.115 and 0.140 kWh/m^3, as depicted in Fig. 13, only when the main fixed-speed pump 1 and auxiliary pumps 6 and 7 were combined with the main variable-speed pump 4. The optimized specific power could be estimated as 0.120 kWh/ m^3, lower than the average of 0.123 kWh/ m^3, which was able to save approximately 2.5 % through pump scheduling. The operating data of the pump combination conditions were evaluated under a limited pump selection scenario. Therefore, the operation of diverse pump combinations in the future requires the evaluation of efficiency, head, and power consumption under each pump operation and operational data under diverse combination conditions. Thus, optimal pump scheduling is recommended to reduce the pump wear and annual power consumption.

4.3. Evaluation of the continuous operation of a pump management system

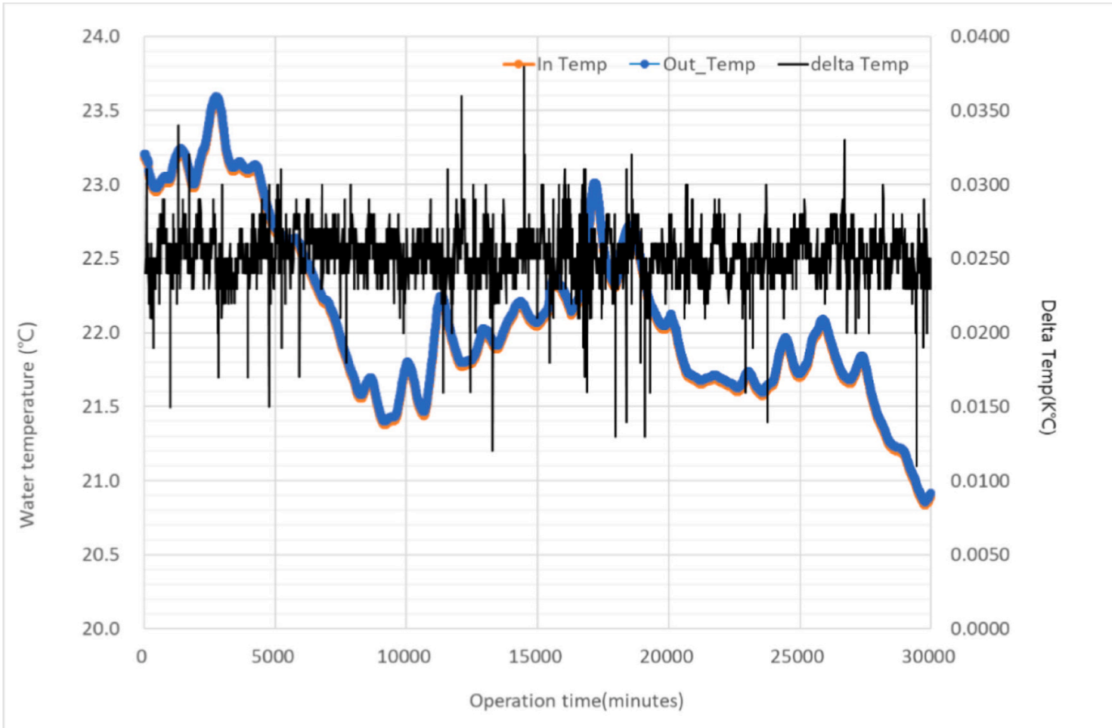
The pump management system can monitor real-time performance of individual pumps. Therefore, operating data should be collected from all possible individual pumps and various pump combination conditions by changing the current pump combination conditions utilized in the G WTP. In this study, the pump combination conditions were scheduled such that the constant-speed and auxiliary pumps could be combined with the two main pumps with variable fluid coupling, and the scenario was constructed to be operated at one-week intervals according to each condition. According to the evaluation of the specific power to the flow rate under diverse combination conditions, it was verified that the specific power was stable when operating in the range of 7800–10,100 m^3/h, as depicted in Fig. 14. As shown in Fig. 10, an analysis of operational data before the establishment of the pump management system revealed a pump combination condition, wherein the specific power was high at a flow rate of less than 7800 m^3/h. Furthermore, another pump combination condition was confirmed to increase the power consumption under flow conditions above 10,100 m^3/h. Alternatively, it was verified that under the same flow rate conditions, the specific power increased by up to 17 %, depending on the pump combination conditions.

Table 3 summarizes the pump efficiencies for diverse pump combinations. When pump 4 was operated in combination with pumps 1, 2, and 3, the pump combination of pumps 4 and 1 had the best energy savings of 15 %. The best energy saving was obtained with the combined conditions of pumps 5 and 1 when pump 5 was majorly used. Additionally, the parallel pump operation using pump 5 as the major function resulted in better energy savings than that obtained with pump 4, indicating better performance of pump 5. It was also shown that the combination of pumps 4 and 5 could operate 11 % more efficiently than the combination of pump 4 and 3. These results suggest that the real-time flow rate patterns could be utilized to optimize the pump.

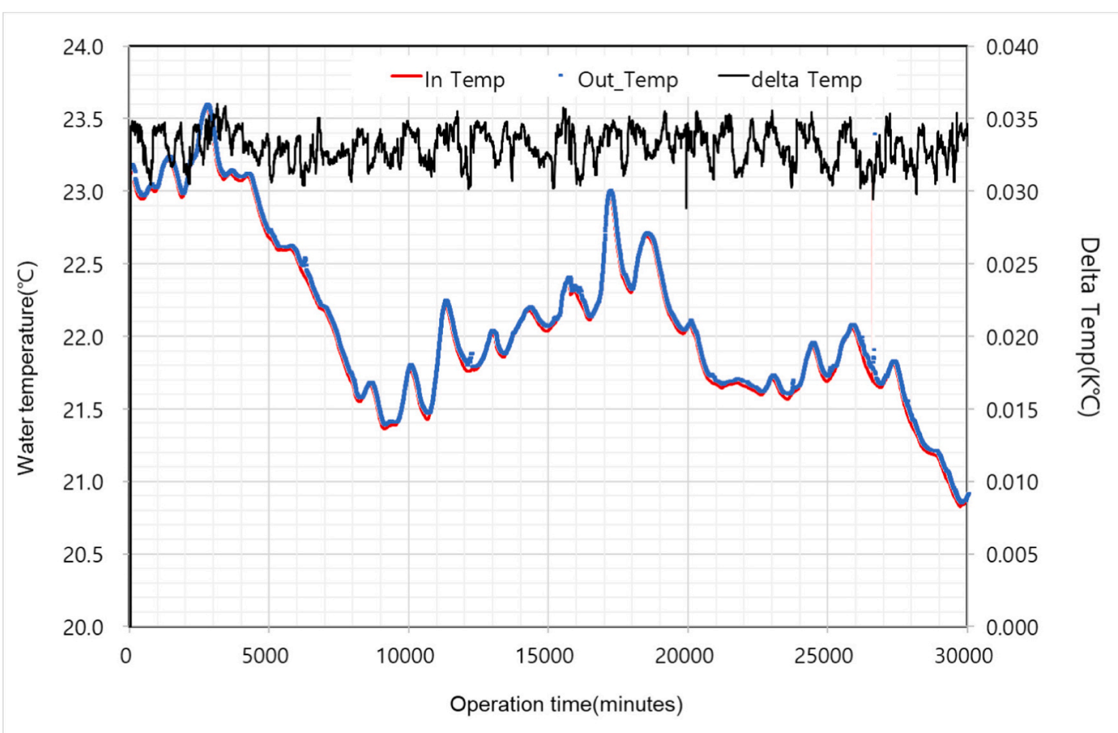
The difference between the flow measurements and thermodynamic flow computations was evaluated. The thermodynamic computations were somewhat higher than the field flow measurements with the electronic flow meter, as depicted in Fig. 15, but the difference in the flow rate was very small. It was considered that the deviation in the flow rate was due to the measurement and correction of the electronic flowmeter at the site and the structural characteristics of the water supply pipe system. If the flow rate is measured to be lower, the pump efficiency will eventually be undervalued, which could result in excessive expenses when diagnosing the pump.

5. Discussions

Deep-learning technologies, genetic algorithms, and thermodynamic measurements have been studied to overcome the limitations of hydraulic pump performance measurements. Thermodynamic pump performance measurement technology is a solution that can optimally manage pumps and save energy by monitoring the performance of individual pumps based on sensing and operation data. By measuring the performance of individual pumps in real time utilizing sensors and algorithms, it was verified that the pump can be scheduled with an optimal pump combination in response to variations in the supply flow rate. When the Green New Deal and carbon reduction targets are imminent, water companies are expected to have a high requirement to reduce power consumption in WTPs, and research results and operating data obtained through this research are expected to be useful to related industries. However, the pump scheduling algorithm based on



(a) Main Pump 1 with a fixed speed



(b) Main pump 4 with a variable speed

Fig. 10. Differential temperature between the suction and delivery of pumps.

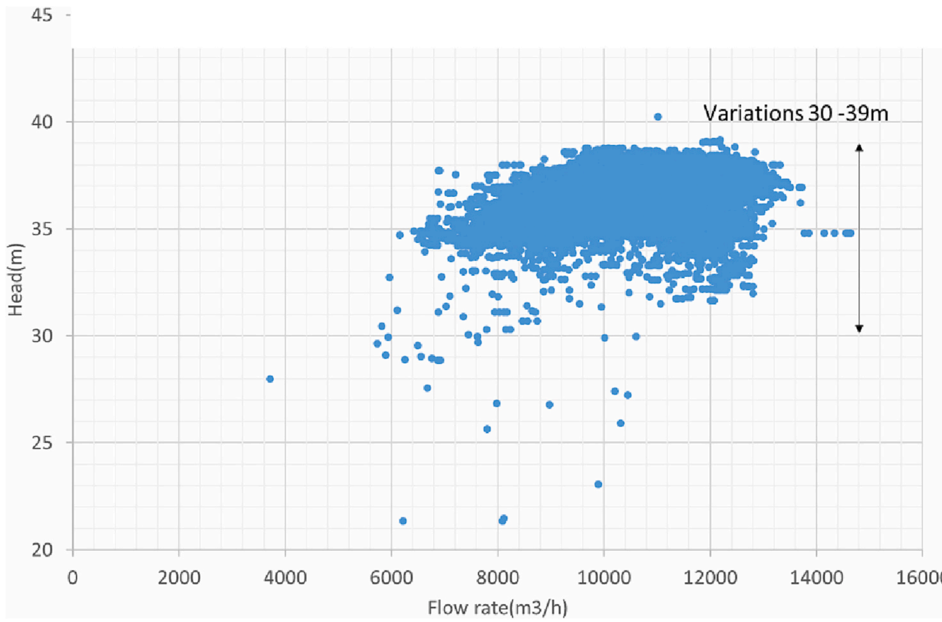


Fig. 11. Variation of total head according to flow rate.

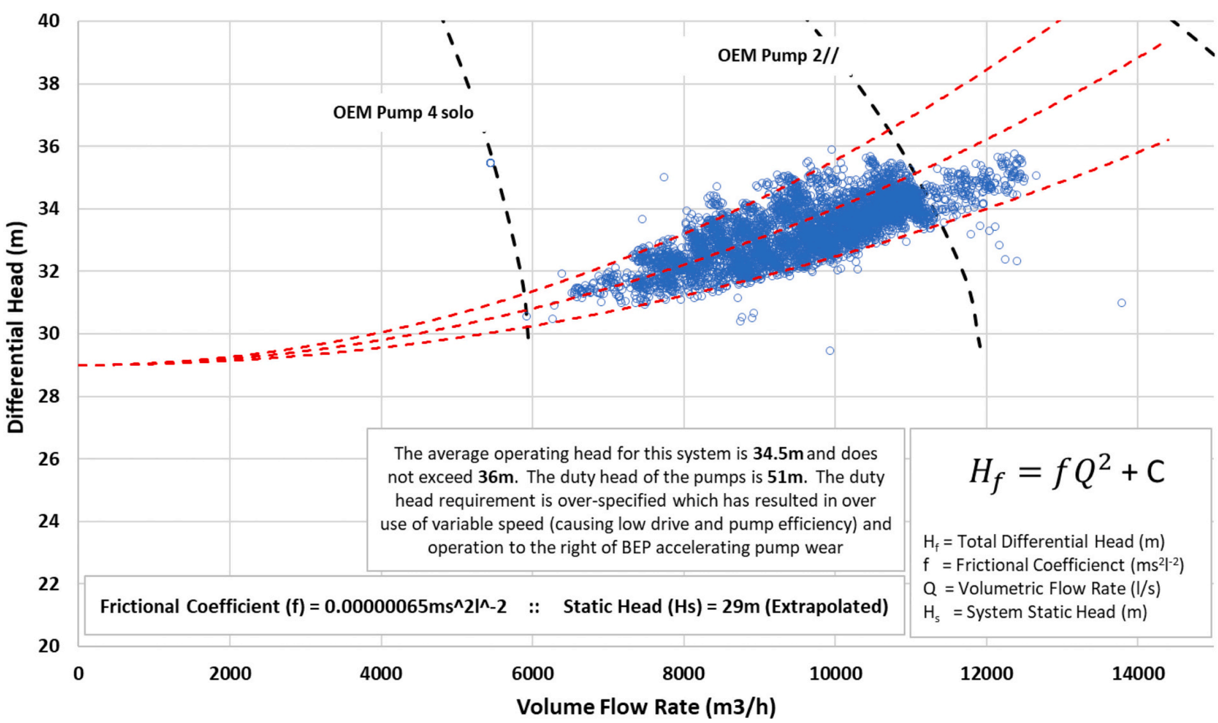


Fig. 12. Characteristics of the total head of the pump according to the flow rate.

thermodynamic measurements is not compatible with all pump stations as the types of pump stations, such as water supply and transmission, vary depending on the purpose. Therefore, the pump scheduling developed in this study should be modified to suit other pump stations. Nevertheless, this thermodynamic method can compute the flow rate and performance of individual pumps, even during operation, which is considered useful for diagnosing real-time pumps and establishing future pump replacement and repair plans.

6. Conclusions

This study focused on optimizing pump scheduling through real-time monitoring utilizing smart temperature sensors, wireless low-power data communicators, and pump data analysis algorithms installed in water supply pumps. The real-time operating data obtained from these sensors were used to compute the flow rate and performance of individual pumps at the pump station where individual electronic flow meters were not available. Seven scenarios of parallel pump operations were evaluated by combining pumps with diverse discharges, and the performance and specific power of the seven cases were evaluated. The

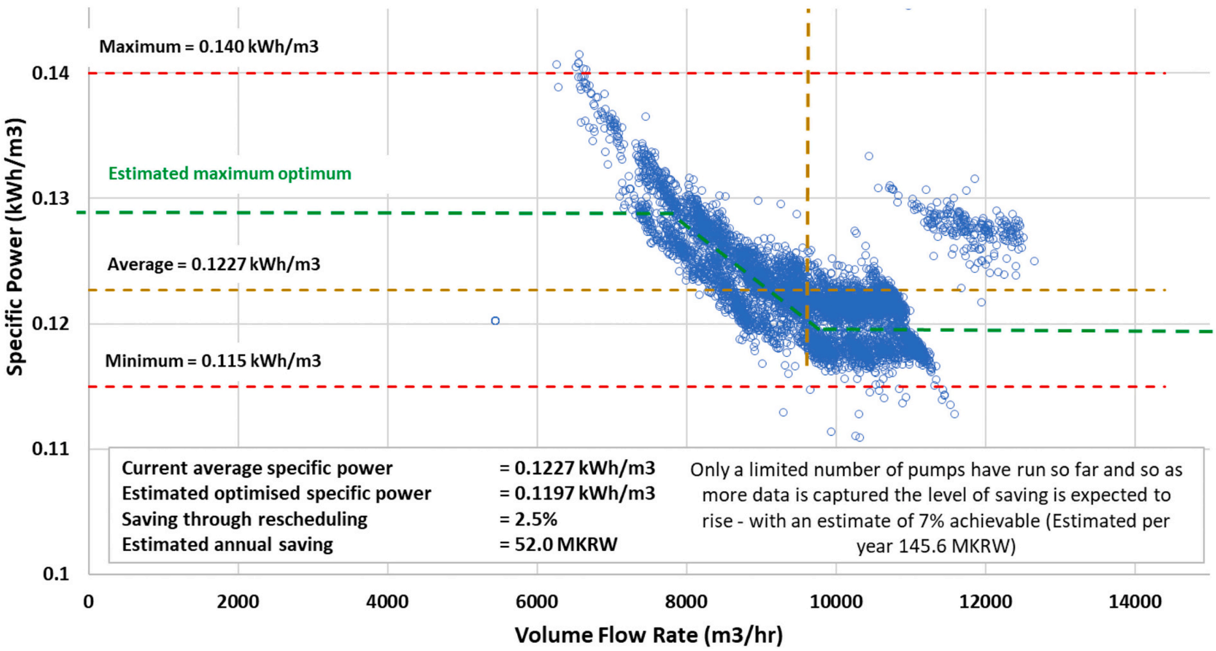


Fig. 13. Specific power analysis according to parallel operation with pump 1, 4, 6, and 7.

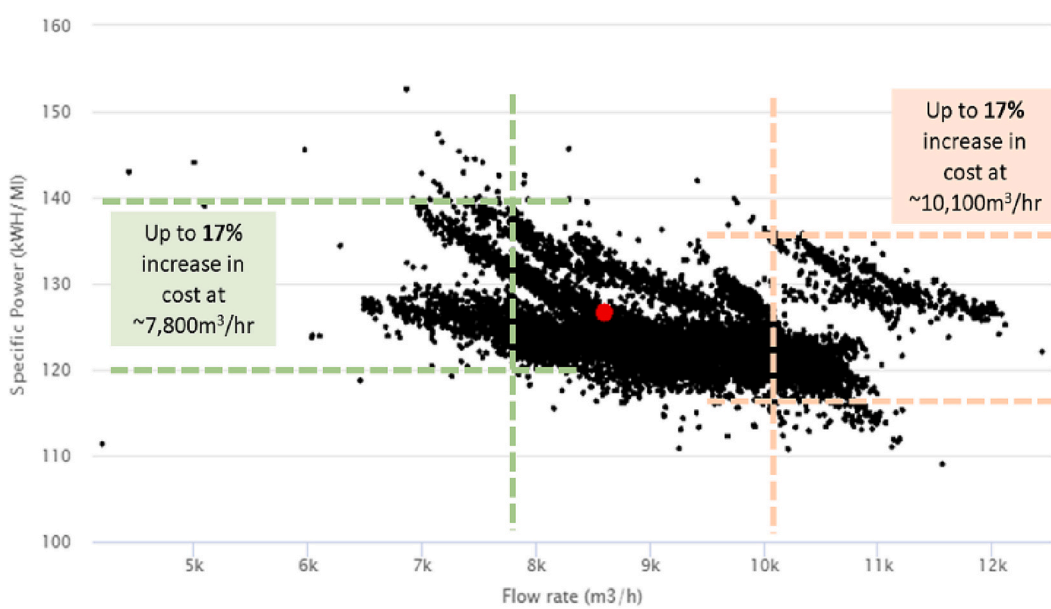


Fig. 14. Specific power analysis under diverse parallel pump operation.

Table 3
Comparison of energy saving according to various parallel pump operation scenarios.

MV pump	Flow rate (m^3/h)	Speed (rpm)	Head (m)	Pump efficiency (%)	MF/MV pump	Flow rate (m^3/h)	Speed (rpm)	Head (m)	Pump efficiency (%)	Energy saving (%)
4	3796	620.0	32.7	78.5	1	6093	699.8	33.3	85.8	15
4	3510	609.4	32.3	77.0	2	5639	700.0	33.1	77.5	8
4	3185	600.2	32.3	75.2	3	5644	581.8	32.4	68.3	0
5	3299	604.7	32.8	78.4	3	5659	419.6	32.3	68.0	2
5	3718	620.2	32.8	80.0	2	5687	700.0	32.9	77.5	13
5	4598	656.4	33.2	82.3	4	4541	646.6	33.1	80.5	11
5	3900	620.0	32.7	78.6	1	6093	699.8	33.3	85.5	15

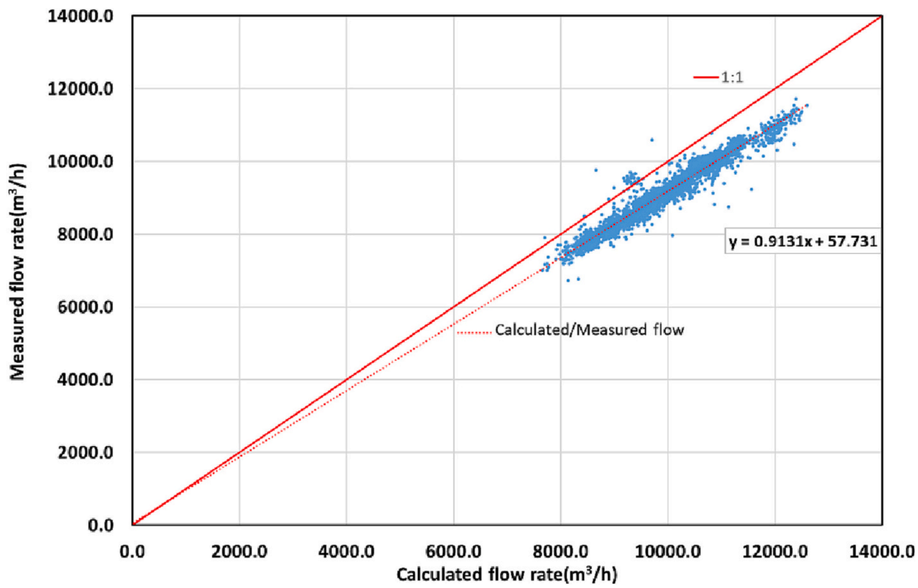


Fig. 15. Comparison between flow measurement and computation.

results showed a specific power difference ranging from 0.115 to 0.140 kWh/m^3 in the flow rate range of 7800 to 1100 m^3/h. To minimize this gap, an optimum pump combination was necessary. However, when operating at less than 7800 m^3/h and above 10,000 m^3/h, the deviation in specific power was 17 % or more. Analysis of various parallel pump operations using the thermodynamic measurements suggested that energy could be reduced by up to 15 % through optimal pump scheduling. In the future, pump scheduling optimization can expand to control the water level in reservoirs in respond to water demand. Sensor-based pump scheduling will be an affordable solution in establishing carbon-neutral waterworks facilities. It economically integrates sensors, data collection and optimization algorithms into existing hardware in waterworks, ultimately leading to improved pump system performance, energy saving, and maintenance support, all while minimizing installation costs.

CRediT authorship contribution statement

Heekyong Oh: Conceptualization, Methodology, Validation, Analysis, Investigation, Writing - Original draft preparation, Editing. Inho Guk: Validation, Resources, Supervision. Shinho Chung: Writing-Reviewing, YongSoo Lee: Editing

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Heekyong oh.

Data availability

The data used in this study is third party and is publicly hosted by the Waterworks of Inchoen Metropolitan City. All other data is included in the paper. The nature of these data means that they are only available internally to the Waterworks of Inchoen Metropolitan City (WIM). Additional approval may be obtained via formal application to the WIM for a specific research project. However, interest parties are advised to contact the corresponding author (heekyong.oh@uos.ac.kr) to discuss the application.

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