

# Optimizing Electric Power Consumption in a Climate-changing Environment: A Study of the Conventional Activated Sludge Process

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**Abstract.** Municipalities' most commonly applied wastewater treatment technology is the conventional activated sludge process (ASP). The challenge is that the ASP consumes high levels of electric power, which results in high electric energy consumption. The power consumption can be attributed to the air blowers/pumps that function non-stop to supply oxygen for the survival of microorganisms in the ASP. This study proposes optimizing electric pump power consumption in the ASP. Multilayer perceptron (MLP) Artificial Neural Network (ANN) algorithm was used to develop the pump power consumption optimization model. Particle Swarm Optimization (PSO) algorithm was applied to optimize the electric pump power consumption. The PSO algorithm output an optimal solution of 0.057396 kW after performing 1000 iterations. The percentage difference between the measured electric pump power consumption (0.087 kW) in the ASP and the optimized electric pump power consumption (0.057396 kW) was 34.03%. This significant difference implies that the PSO algorithm performance was satisfactory in optimizing the electric pump power consumption.

## 1. Introduction

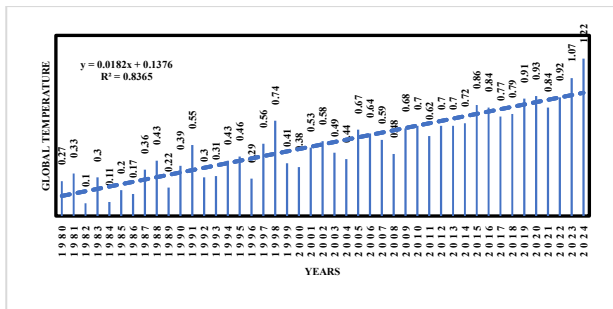
The conventional activated sludge process (ASP) is municipalities' most commonly applied wastewater treatment technology 1. A conventional ASP consists of an aeration chamber where microorganisms are suspended, a clarifier, and a recycler that returns active microorganisms to the aeration chamber 2. The activated sludge aeration chamber consists of either surface aerators or diffused aerators. In the case of diffused aerators, an air blower is utilized to pump air into the aeration chamber for the respiration and survival of microorganisms 3. Air blowers in the ASP consume high levels of electric power, which results in high energy consumption 4.

In a medium-sized wastewater treatment plant (WWTP), with a 27000 cubic meters per day (m<sup>3</sup>/d) flow rate, the average electric pump power consumption was reported to be 1166.667 Kilowatts (kW) daily in the ASP 5. For large-size WWTPs, 6 reported a total of 9833 kW electric power consumption in the Castiglione Torinese plant, in Italy. This was based on an energy consumption of 0.4 kWh/m<sup>3</sup> and a 590 000 m<sup>3</sup>/d flow rate. Similarly, 7 reported 3333.333 kW electric power consumption in medium – large Mashhad WWTP, which has a daily flow rate of 80 000 m<sup>3</sup>/d. For small-sized WWTPs with a flow rate of 678 m<sup>3</sup>/d, the electric power consumption was reported to be 42.375 kW, and the energy consumption

was 1.5 kWh/m<sup>3</sup> 8. A WWTP in Österröd, Sweden, designed to service 30 000 residents utilized 100 kW electric power, resulting in 0.08 kWh energy consumption 9. The electric power consumption is high and compromises Sustainable Development Goal (SDG) No. 7. SDG 7 encourages high energy users such as WWTPs, to minimize the energy consumed during the aeration process.

The power consumption can be attributed to the air blowers/pumps that operate non-stop to supply oxygen for the survival of microorganisms in the ASP 4. Oxygen is not soluble in wastewater; hence, continuous aeration is essential to maintain oxygen mole fractions in the wastewater. In addition, climate change will contribute to poor oxygen supply and solubility in the ASP. Reference 10 defined climate change as an ongoing transformation in the meteorological conditions on the earth's surface, prompted by greenhouse gas (GHG) emissions from engineered systems and human actions. Reference 11 reported that climate change has been shown to affect fresh and surface water temperatures on the earth's surface. The global temperature increase from the years 1980 – 2024 is shown in Fig. 1 12.

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**Fig. 1.** Global temperature increase 12

The increase in wastewater temperature will hinder oxygen solubility, forcing plant operators to increase airflow supply, resulting in higher electric pump power consumption. Reference 13 reported a 37.4% drop in dissolved oxygen (DO) concentration when temperatures were raised. DO concentrations decreased from 13.1 – 8.2 mg/L between 5 – 25°C temperature respectively. Similarly, temperature increase from 7 – 35°C, resulted in a 12 – 2% DO saturation drop. Likewise, when the temperature of water is increased by 1°C, DO concentration drops by at least 2.3% 14. Authors 16 stated a 2.1 mg/L DO concentration decline due to a temperature increase (20 – 35°C). Lastly, reference 15 reported a 2 mg/L DO concentration decrease when temperature increased from 18.1 – 24.6°C respectively.

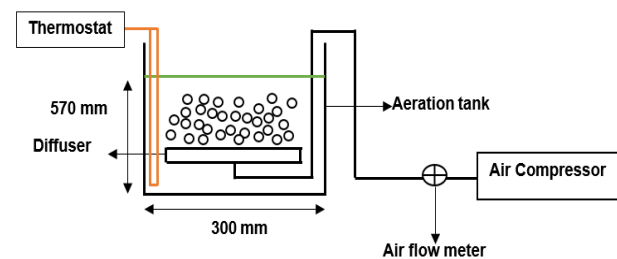
Different researchers have attempted to solve the energy consumption problem in WWTPs with success. However, most of the researchers did not consider the impact of climate change which affects DO concentration. Reference 17 reported used low-frequency electric field and achieved an energy saving of 30%. Although the effect of temperature was considered, the airflow supply was not reported which limits the measurements of GHG emissions that emanate from the air blowers. Reference 18 attempted to minimize energy consumption using rational design and engineering strategies. The authors opted to change the treatment method from aerobic to anaerobic which reduced energy consumption from 1 kWh/m<sup>3</sup> to 0.58 kWh/m<sup>3</sup>. This was a 42% decrease in energy consumption, however, changing a treatment technology is an expensive exercise. Lastly, the authors 19 advanced control strategies to reduce energy consumption and achieved 7% energy consumption decrease. The advanced controllers were used to monitor effluent ammonia and DO concentration. Although it was effective, climate change effects were not considered, which has a direct impact on the nitrification process.

Because of the high electric pump power consumption and climate temperature changes, this study proposes the optimization of electric pump power consumption in the ASP. The optimization problem will include temperature variations, which, will account for the climate-changing environment, that suppresses DO concentration in the ASP. Optimizing electric pump power consumption will contribute to achieving SDG No: 7: ensuring access to affordable, reliable, sustainable, and modern energy.

## 2. Materials and methods

### 2.1 Experimental process

Laboratory scale simulation of the ASP was carried out at the Department of Civil Engineering, Faculty of Engineering and the Built Environment, Tshwane University of Technology to develop an electric pump power optimization model in the ASP. The climate temperature range chosen for this study was 15 – 35°C, with an increment of 2.5°C. The airflow supply chosen ranged from 5 – 30 L/min. The laboratory scale schematic ASP diagram is presented in **Fig. 2**.



**Fig. 2.** Laboratory scale schematic ASP diagram

### 2.2 Wastewater collection, analysis, and disposal

The 17 process was followed for collecting wastewater at the WWTP. Two samples were collected daily to avoid any biological activities during storage. A 25-litre cylinder was utilized to collect the raw wastewater. The active sludge was collected from the return-activated sludge reactor. Ice cooler at a temperature of 4°C was used as storage for the wastewater, ensuring no biological activities occur. Two wastewater characteristics were analyzed: DO and COD concentration. The Standard Methods for the Examination of Water and Wastewater were utilized to analyze wastewater characteristics. After the aeration process, wastewater was flushed into the laboratory ablation blocks. The discarding technique allowed the wastewater to return to the WWTP.

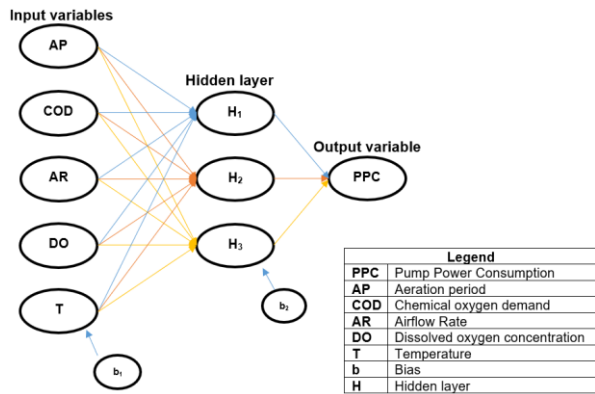
### 2.3 Electric power consumption

Electric power consumption was measured in kilowatts (kW). The electric pump power output was measured using a Watt meter. The digital wattmeter is also equipped with a timer, which was used to monitor the aeration period.

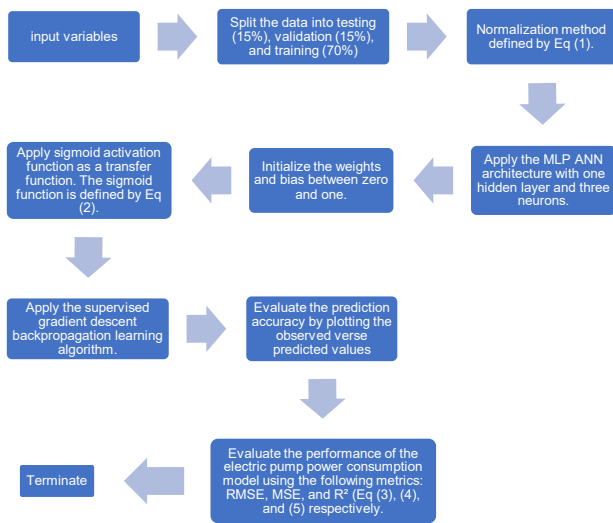
### 2.4 Application of Multilayer Perceptron Artificial Neural Network Algorithm

The electric pump power consumption optimization model was developed using the Multilayer perceptron (MLP) Artificial Neural Network (ANN) algorithm. Temperature (T), DO concentration, Airflow Rate (AR), Chemical Oxygen Demand (COD) concentration, and Aeration Period (AP) were input variables used to develop the electric pump power consumption model as shown in

**Fig. 3.** In addition, **Fig. 4** shows a flowchart that defines ten steps followed in the application of the MLP ANN algorithm to model electric pump power consumption in the ASP.



**Fig. 3.** Pump Power Consumption MLP ANN architecture



**Fig. 4.** MLP ANN flow chart procedure

$$x(\text{scaled}) = \frac{x - \min_x}{\max_x - \min_x} \quad \text{Eq. (1)}$$

$$f = \frac{1}{1 + e^{-x}} \quad \text{Eq. (2)}$$

$$MSE = \frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{N} \quad \text{Eq. (3)}$$

$$R^2 = \frac{1}{m} \sum_{j=1}^m \left( 1 - \frac{SSE}{SST} \right) \quad \text{Eq. (4)}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{N}} \quad \text{Eq. (5)}$$

Where  $x(\text{scaled})$  is the scaled data,  $x$  is the data point,  $\min_x$  is the minimum value in the dataset,  $\max_x$  is the maximum value in the dataset.  $MSE$  is the mean squared error,  $y_i$  is the observed value,  $\hat{y}_i$  is the predicted value,  $R^2$  is the coefficient of determination,  $N$  is the number of data points,  $SST$  is the total sum of squares, and  $SSE$  is the sum of squared error.

## 2.5 Application of particle swarm optimization algorithm

The Particle Swarm Optimization (PSO) algorithm Pseudo code shown in Table I was followed to optimize the electric pump power consumption model. The position and velocity of each particle in the search space were updated using Eq. (6) and Eq. (7) respectively.

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \quad \text{Eq. (6)}$$

$$v_{ij}(t+1) = w \times v_{ij}(t) + c_1 r_1 (pbest_{i,j} - x_{i,j}(t)) + c_2 r_2 (gbest_j - x_{i,j}(t)) \quad \text{Eq. (7)}$$

Table I: Particle swarm optimization PSEUDO CODE

Particle Swarm Optimization (PSO) Algorithm	
1.	Initialize the number of particles $N$ , particles' position ( $x^i$ ), velocity ( $v^i$ ), previous best position ( $p^i$ ),
2.	While ( $t < \text{maximum number of iterations (T)}$ ) do
3.	For all Particles ( $i$ ) do
4.	Calculate the fitness function for the current position $x^i$ of the $i^{\text{th}}$ particle ( $F(x^i)$ )
5.	If ( $F(x^i) < F(p^i)$ ) then
6.	$P^i = x^i$ end if
7.	If ( $F(x^i) < F(G)$ ) then
8.	$G = x^i$
9.	End if
10.	Adjust the velocity and positions of all particles according to equations Eq. (6) and Eq. (7) respectively.
11.	End for
12.	Stop the algorithm if a sufficiently good fitness function is met
13.	End while

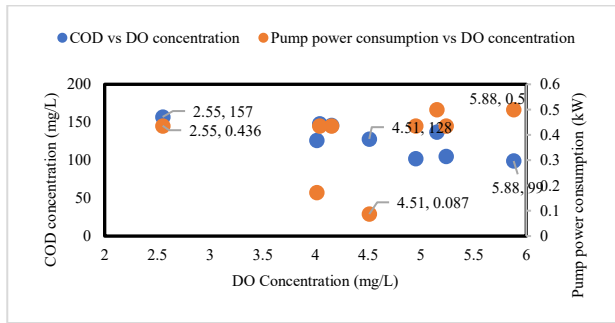
## 3. Results and discussions

### 3.1 Electric pump power consumption during COD removal and DO concentration results

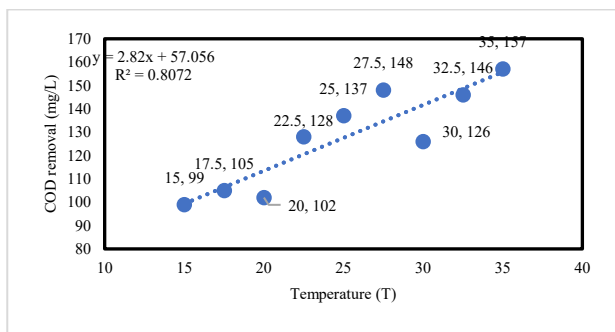
Fig. 5 presents the relationship between COD, DO concentration, and electric pump power consumption during the aeration process. The results show that the highest COD removal (157 mg/L) was obtained while operating the ASP at 2.55 mg/L DO concentration which consumed 0.436 kW of electric power. The high COD removal at low DO concentration was influenced by high wastewater temperatures (35°C) as shown in Fig. 6. High temperatures have been reported to suppress DO concentration and improve the metabolic rate of microorganisms in the ASP 21, 22, 23. Hence at higher temperatures, high COD removal was attained as a result of an increased metabolic rate of microorganisms 24, 25.

The second highest COD removal (148 mg/L) was obtained while operating the ASP at 4.51 mg/L DO concentration which consumed 0.087 kW of electric power. In this case, COD removal was achieved at a higher DO concentration (4.51 mg/L) and higher wastewater temperature (27.5°C) as shown in Fig. 5 and Fig. 6. The influence of climate temperature change is noticeable on DO concentration and COD removal in the aeration chamber. The lowest measured electric power consumption (0.087 kW) by the air pumps used during

COD removal in the ASP is high and should be optimized to meet SDG No: 7.



**Fig. 5.** Relationship between DO concentration, COD, and Pump power consumption in the activated sludge process

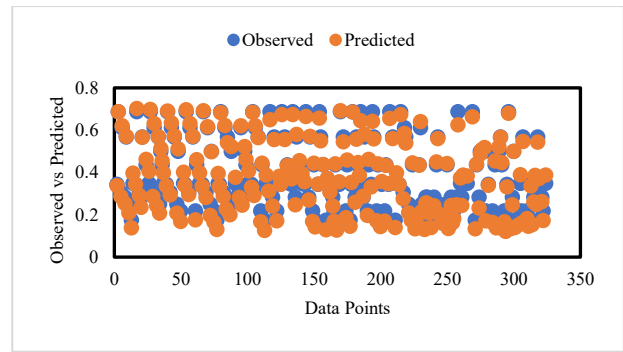


**Fig. 6.** Relationship between COD removal and temperature variations

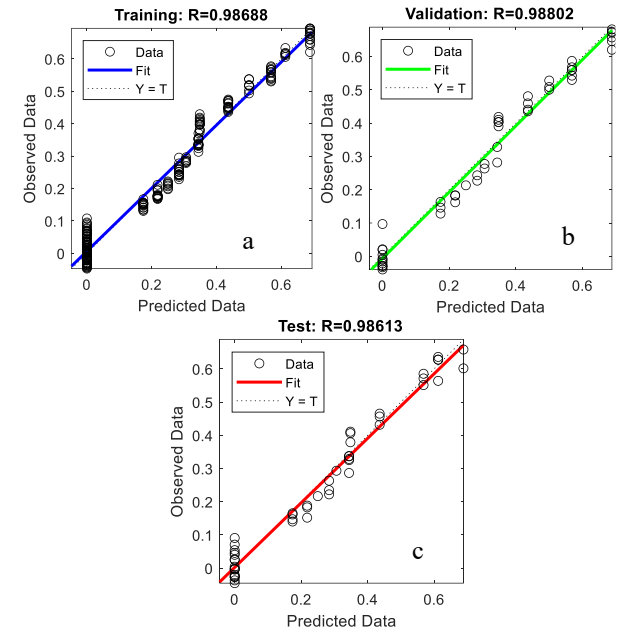
### 3.2 Modelling prediction accuracy and performance evaluation

The MLP ANN algorithm was able to map the observed data correctly. **Fig. 7** shows 324 observed electric pump power data which was on par with the predicted electric pump power consumption data. This shows that the MLP ANN algorithm modeled the electric pump power consumption data correctly. This can also be supported by the RMSE, MSE, and  $R^2$  results obtained in **Fig. 8** and **Fig. 9** respectively.  $R^2$  values were 0.98688 (training), 0.98802 (validation), and 0.98613 (testing). This means that overall, 98% of the observed electric pump power data was predicted correctly by electric pump power optimization model. This confirms that the MLP ANN algorithm coupled with the sigmoid transfer function modelled the data accurately.

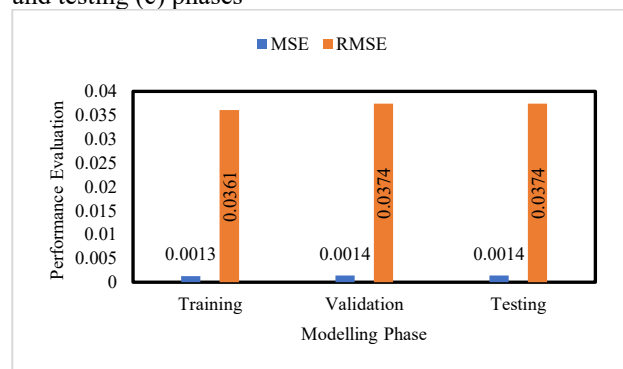
The sigmoid function provides a smooth gradient which supports the output values 25. This shows that the MLP ANN algorithm is a robust algorithm that can model nonlinear data efficiently and effectively. The RMSE were 0.0361 (training), 0.0374 (validation), and 0.0374 (testing), which was lower than the value of one. Similarly, MSE during training, validation, and testing phases were 0.0013, 0.0014, and 0.0014 respectively, which was lower than the value of one. The RMSE and MSE results imply that the error difference between the observed and predicted electric pump power data was minimal.



**Fig. 7.** Observed vs Predicted data



**Fig. 8.**  $R^2$  values during the training (a), validation (b), and testing (c) phases



**Fig. 9.** RMSE and MSE performance results

### 3.3 Optimization results

A single objective electric pump power optimization function was considered and is defined in Equation Eq. (8).

$$\text{Min } [Y_i(AP, COD, AR, DO, T)] \quad \text{Eq. (8)}$$

Where  $T$  is the temperature,  $DO$  is the dissolved oxygen concentration,  $AR$  is the airflow rate,  $COD$  is the chemical oxygen demand,  $AP$  is the aeration period, and  $Y_i$  is the electric pump power optimization model. The constraints are listed in Eq. (9) – Eq. (13)

$$1 \leq AP \leq 2 \quad \text{Eq. (9)}$$

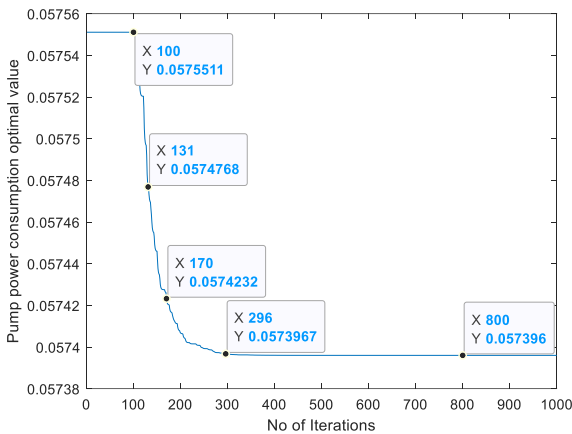
$$30 \leq COD \leq 75 \quad \text{Eq. (10)}$$

$$1 \leq AR \leq 5 \quad \text{Eq. (11)}$$

$$1 \leq DO \leq 2 \quad \text{Eq. (12)}$$

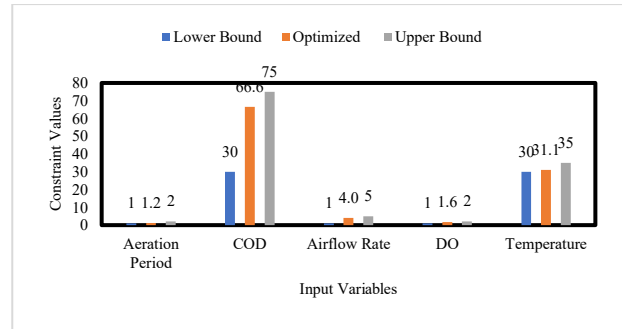
$$30 \leq T^{\circ}C \leq 35 \quad \text{Eq. (13)}$$

**Fig. 10** presents the relationship between electric pump power optimal value results and the number of iterations. PSO algorithm successfully minimized the electric pump power consumption to find the global optimal solution subject to constraints. The PSO algorithm produced a global optimal solution of 0.057396 kW after performing 1000 iterations as shown in **Fig. 10**. The percentage difference between the measured electric pump power consumption (0.087 kW, section 3.1) in the activated sludge during COD removal and the optimized electric pump power consumption (0.057396 kW) was 34.03%. This significant difference suggests that the PSO algorithm performance was satisfactory in improving the electric pump power consumption in the activated sludge. Plant managers can use the optimization model to reduce the electric pump power consumption during the aeration process. A study conducted by 17 reduced energy consumption by 30%, which was motivated by the stimulating microbes present in the ASP, thereby reducing operation time. Energy consumption results were in line with the results in the current study. A similar study obtained 70% energy consumption reduction, which was achieved by changing from aerobic to anaerobic treatment processes 18. The results were higher compared to the current study, however, changing treatment technology is expensive and requires a completely new design. The application of the fuzzy control system in the nitrification process achieved energy consumption reduction of 7% 19.



**Fig. 10.** Pump power consumption optimal value

**Fig. 11** presents the decision variables' output results obtained during the optimization process. The results indicate that when the activated sludge process is operated for 1.2 hours, at an airflow rate of 4 L/min, and a temperature of 31.1°C, the total electric pump power consumption results will be 0.057396 kW. The electric pump power consumption saving was achieved without violating effluent COD concentration quality, which was 66.6 mg/L, as shown in **Fig. 11**.



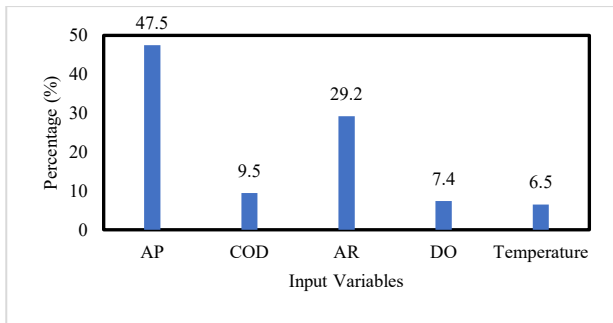
**Fig. 11.** PSO algorithm optimized output results

### 3.4 Cost-benefit analysis

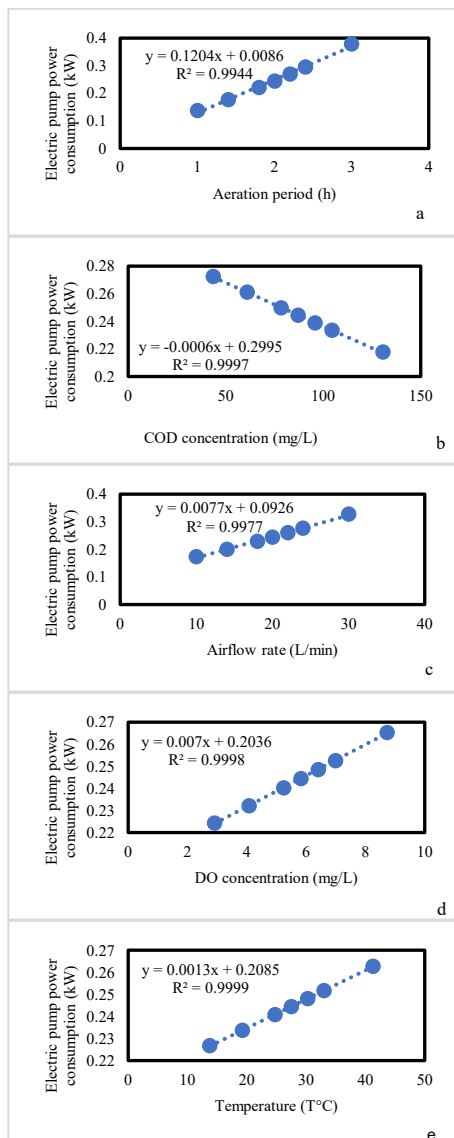
The application of the PSO algorithm will reduce the operational cost of the conventional ASP. In South Africa, electric power costs 207.5 cents/kWh, R2.075 kWh (South African Rand). The pump's electric power consumption before optimization was 0.087 kWh after a four-hour aeration period, which results in 0.022 kWh for one hour of aeration. If the conventional ASP is operated for 24 hours, the electric power consumption will be 0.522 kWh. This will result in an operational cost of R1.083 for purifying 25 litres of wastewater, which is equivalent to R0.043/L/d. The Daaspoort WWTP in the City of Tshwane has a capacity of 55 megalitres/day, which will cost R2,365,000.00. The optimized electric pump power consumption (0.057396 kW) will result in a cost of R1,572,076.44, which produced a saving of R810,853.6. Therefore, it was essential to optimize electric pump power in the conventional ASP to ensure low operational cost.

### 3.5 Sensitivity analysis

**Fig. 12** presents electric pump power consumption input variables sensitivity analysis results. Aeration period (47.5%) and airflow rate (29.2%) were the biggest drivers of high electric pump power consumption in the ASP. This was because the extended hydraulic retention time and continuous airflow supply in the ASP result in high electric pump power consumption. The results can be supported by **Fig. 13** (a) and (c). The rate of change between electric pump power consumption, aeration period (0.1204), and airflow rate (0.0077) were the highest overall. Temperature (6.5%) on the other hand was the lowest contributor towards the electric pump power consumption. However, the rate of change between electric pump power consumption and temperature was positive 0.0013. This indicates that when the temperature of wastewater increases as a result of climate change, more electric power will be required for the airflow supply to maintain DO concentration in the ASP. Optimizing electric pump power consumption in a climate-changing environment was essential.



**Fig. 12.** Input Variables Sensitivity Analysis



**Fig. 13.** Relationship between Electric pump power and input variables output from MLP ANN model

#### 4. Conclusion

Air blowers in the ASP consume high levels of electric power, which results in high energy consumption. The highest COD removal (157 mg/L) was obtained while operating the ASP at 2.55 mg/L DO concentration which consumed 0.436 kW of electric power. The second highest COD removal (148 mg/L) was obtained while operating the ASP at 4.51 mg/L DO concentration which

consumed 0.087 kW of electric power. Particle Swarm Optimization (PSO) algorithm was utilized to optimize the electric pump power consumption. The PSO algorithm produced a global optimal solution of 0.057396 kW after performing 1000 iterations. The percentage difference between the measured electric pump power consumption (0.087 kW) in the activated sludge during COD removal and the optimized electric pump power consumption (0.057396 kW) was 34.03%. This significant difference implies that the PSO algorithm performance was satisfactory in optimizing the electric pump power consumption.

#### 5. Acknowledgment

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