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An overview of the biological ammonia treatment, model prediction, and control strategies in water and wastewater treatment plant

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Abstract

Water disruption has always been a major issue in Malaysia. The reason for the frequent water disruption is due to the shutdown of water treatment plant (WTP) for unable to process contaminated raw water from the river. In wastewater treatment plant (WWTP), main source of ammonia is from the breakdown of proteins and amino acids in organic waste. Typically, ammonia is not fully removed from the WWTP and most of the ammonia is being discharged together with the plant effluent into the river streams. High levels of ammonia in the water exerts an oxygen demand which causes oxygen depletion. Hence, affecting the aquatic ecosystem and creates a toxic environment for the aquatic life. Biological treatment is known to be the most cost saving method as it only constructs of simple components, chemical free treatment and producing no harm by-products which later cause cost increment for additional treatment. Furthermore, biological treatment is capable in producing high quality treated drinking water that meets the standard water guidelines and regulations. In this paper, the aim is to conduct an overview on the application of biological treatment as an alternative treatment method of ammonia removal in water and wastewater treatment plant. This overview presents the cohesive approach of biological treatment in water and wastewater treatment plant, source of ammonia pollution, standard implies on ammonia concentration to control potential hazards, reported cases and recent pollution status of ammonia globally. In addition, the use of an artificial intelligence for model prediction and control strategies for water treatment have been included in this overview.

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1.0 Introduction

The scarcity of clean water resources should be our utmost attention facing the new era of massive climate changes, mass production and global pandemic. Malaysia has faced water pollution for years now, caused by biochemical oxygen demand (BOD), ammoniacal nitrogen (NH_3–N) and suspended solids (SS) which serve as the major pollutants in Malaysia's rivers and lakes (Yuk et al., 2015). Urbanisation is often related to industrialisation that gives rise to many employment opportunities. This is due to the high demand for labour. However, the impact of industrial revolution and the increase in human population have caused the environment to deteriorate. One of the environmental impacts is increased water pollution and waste disposal. River pollution is often caused by the discharge of domestic sewage, industrial effluents, rapid urbanisation and agricultural activities (Farid et al., 2016; Suratman et al., 2015; Zhang et al., 2018).

River pollution cannot be taken lightly as it can cause water disruption in a community. Ammonia pollution in Johor had caused shutdown of treatment plant and water supply was being cut to 222,000 consumers (Leong, 2017). A study was conducted on analysing the problems of ammonia and manganese in Malaysian drinking water treatments. Based on the assessment, it was reported that three drinking water treatment plants (DWTP) had received high concentration of ammonia from the raw water (Hasan et al., 2011). Raw water is defined as untreated, unprocessed, unfiltered, or unprocessed natural water such as groundwater, spring water, rainwater, or water from streams, lakes and rivers (Nall, 2018; Young, 2018). Ammonia is toxic substances that can affect the human health. Although at low concentration of ammonia in water is non-toxic to human, but long-term ingestion of drinking water containing more than one mg/L (ppm) ammonia may lead to ammonia poisoning and can cause damage to our internal organ systems. Access to clean drinking water is a major concern nowadays. The raw water quality is mainly influenced by the presence of pollutants such as pathogens (bacteria, fungi, viruses, and parasites), inorganic compounds (magnesium, nitrate, chloride, sulphate, sodium, iron), and organic material (sludge) in the water supply (Al-Mamun & Zainuddin, 2013). The presence of ammonia can be detected through unpleasant smell like urine or sweat. There are many approaches to remove ammonia in WTP and WWTP and some of the known methods are ion-exchange, air stripping, biological treatment, microwave radiation, supercritical oxidation (Adam et al., 2019), biological sand filter (BSF), biological activated carbon (BAC), trickling filter, biological aerated filter (BAF), membrane bioreactor (MBR), moving bed biofilm reactor (MBBR) and fluidised bed biofilm reactor (FBBR) (Abu Hasan et al., 2020; Karri et al., 2018; Mook et al., 2012). Water treatment technologies widen and create more accessibility to clean water. However, even with the current treatment technologies, there are still millions of people who lack access to clean water especially those in the least developed countries who may suffer from infectious diseases including diarrhoea, hepatitis A, typhoid, polio, and cholera. This problem may also aggravate malnutrition and childhood stunting. Without access to clean drinking water, a person is forced to rely on untreated surface water or contaminated wells.

Water treatment can be conducted either in households or in a water treatment facility. For household water treatment systems, the methods that are commonly used are boiling, household slow sand filter, and domestic chlorination. Meanwhile, community water treatment system involves storage and sedimentation, up-flow roughing filter, slow sand filtration, and chlorination in piped water-supply systems (World Health Organization, 2018).

A general water treatment plant consists of five major processes that are coagulation and flocculation, sedimentation, filtration, disinfection, and storage – to treat drinking water sources. The treatment starts from the pumping station, where the pump draws water from reservoirs, streams, lakes, or rivers. Water then travels by pipelines from the pumping station to the treatment facility. The first step of the treatment process would be removing sediments and particles from the raw water with the help of coagulants such as liquid aluminium sulphate (alum) and other chemicals. Coagulants cause particles in the water to stick together and form flocs, which are easier to remove by settling or filtration as it will sink to the bottom during sedimentation (Owodunni & Ismail, 2021). During sedimentation, water flows slowly in the sedimentation tanks causing the floc to settle to the bottom due to its weight. Sludge is formed after the floc has been collected at the bottom of the tank. Since the flocs are not entirely removed by sedimentation, the clear water on top will then pass-through filters which are made of layers of sand, gravel, charcoal, and crushed anthracite to remove fine sized particles such as dust, parasites, bacteria, viruses, and any remaining sediments. The last stage of water treatment is disinfection. Water is disinfected with a small amount of chloramine or chlorine-based compounds such as chlorine dioxide or monochloramine aim to kill bacteria or microorganisms that are present in the water. In addition, chlorination is an effective method to remove ammonia in drinking water (Zhang et al. 2019). Another method of disinfecting water is by ozone treatment. Ozone treatment involves pumping an electric current through the water that causes oxygen molecules to disassociate and combine with a free oxygen molecule forming ozone (O_3). Ozone is a strong oxidant and causes microbes cell walls to leak rapid cell decomposition and overall damage to cells. Hence, pathogenic (disease-causing) organisms are destroyed. Chlorination is much preferable than ozone because it is cheap, an effective disinfectant, and residual chlorine levels remained in the tap water can kill any contaminants that might get introduced after leaving the treatment plant. Lastly, the treated water is stored in a closed tank or placed in a reservoir before being distributed to homes and businesses in the community (Mahajan, 2021). Fig. 1 shows the process of treating drinking water in a water treatment facility.

A wastewater treatment plant is a facility that is designed to treat industrial wastewater for it to be safely discharged back into streams or other receiving waters, or for reuse (Environmental Protection Agency (EPA), 1998). There are primary and secondary treatment in treating wastes. In the primary treatment, the wastewater will flow through a screen, where large floating objects that might clog pipes or damage equipment are removed.

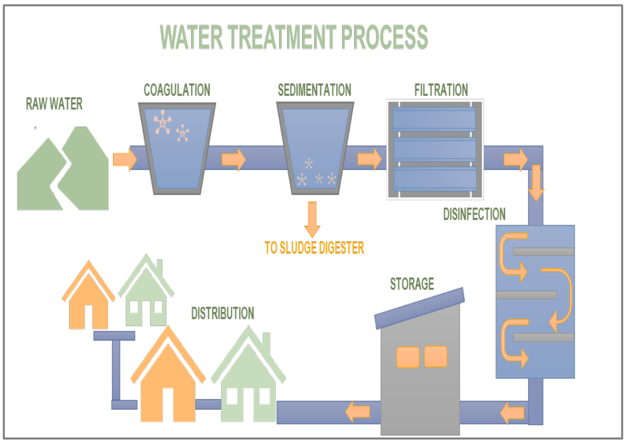

Fig. 1: Water treatment process steps.

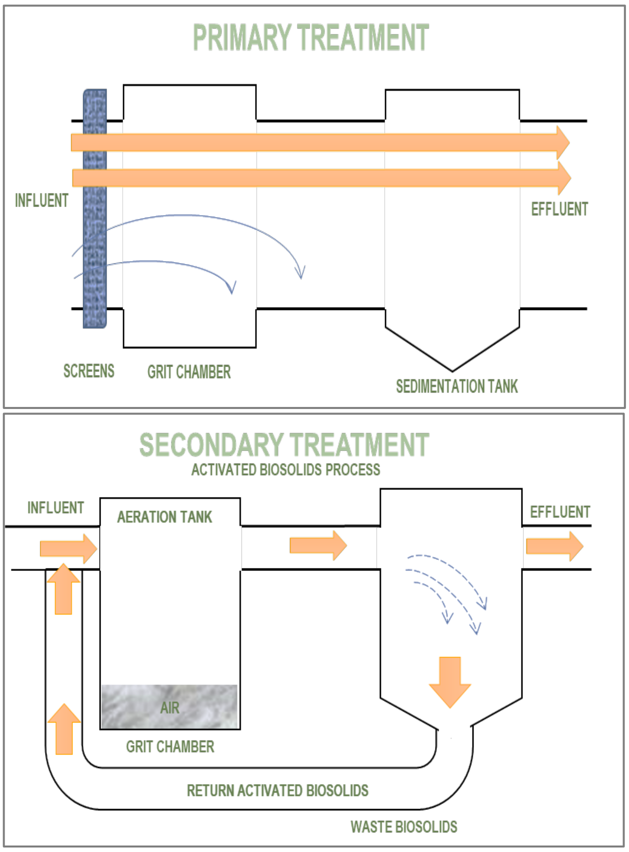

Fig. 2: Primary and secondary treatment of wastewater treatment plant

After the sewage has been screened, it passes into a grit chamber, where cinders, sand, and small stones settle to the bottom. The sewage then enters a sedimentation tank to remove any remaining organic and inorganic matter along with other suspended solids. Sludge is formed when the suspended solids gradually sink to the bottom Meanwhile, secondary treatment is designed to substantially degrade the biological content of the waste through aerobic biological processes in a way that it can be done with biofiltration, aeration and oxidation ponds. Biofiltration employs contact filters, sand filters, or trickling filters to ensure that any additional sediment is removed from the wastewater. Aeration is a long process where it increases the saturation of oxygen by introducing air to the wastewater. It is an effective process that involves mixing wastewater with a solution of microorganisms and is then aerated for up to 30 hours to ensure results. Oxidation ponds are usually used during warm climates. It utilises natural water bodies such as lagoons, allowing wastewater to pass through for a period before being retained for two to three weeks. Instead of using trickling filters, activated sludge is more preferable as it speeds up the rate of waste decomposition in water by bringing together sewage, oxygen and sludge with bacteria. The activated sludge process involves high concentration of microorganisms (bacteria, protozoa and fungi) to degrade organics and remove nutrients from wastewater, producing quality effluent (Peavy et al., 2007). Fig. 2 illustrates two stages of treating wastewater in a wastewater treatment facility.

Common ammonium treatment used in water industry is physiochemical treatment such as ion exchange, activated carbon, adsorption, chemical precipitation, air stripping, membrane filtration, break-point chlorination, and electrochemical technique (Karri et al., 2018). Other treatment such as biological treatment is available however mostly applied in developed country. Perception towards how effective the latter treatment impacted its usage and involvement of microorganism in the treatment create cautiousness especially in drinking water treatment industry (Treacy, 2019). Biological treatment involves the usage of bacteria that aids the decomposition of ammonia through oxidation process (Adam et al., 2019). It forms no by-products and does not require further treatment. Thus, the cost for this operation is lower than physicochemical treatment (Mook et al., 2012).

One of the biological treatments that will be further studied is the application of biosand filter (BSF) in treating ammonia in drinking water and wastewater to ensure the production of clean drinking water and effluent. BSF is an adaptation of the slow sand filter that can be built on a smaller scale, which is often used in households or by the community to gain access to clean drinking water. The BSF is said to be a promising technology according to most studies and it is proven to be operated at the lowest cost. The BSF has also shown that it is capable to produce high quality effluents which met the standards of drinking water quality (Liu et al., 2020; Lakshmi et al., 2012).

In order to enhance the performance of the treatment plants besides the use of an efficient filtration system, there are several control strategies and prediction models that are widely used in the industrial control applications such as Proportional, integral, and derivative (PID) controller, artificial neural network (ANN), and model predictive control (MPC). The conventional PID controller is a typical control system used to regulate the parameters such as temperature, pressure, flow, and other process variables in industrial control applications. ANN is an advanced computing system that is generally used for predicting output values for given input parameters while MPC is also a control algorithm that serves the same function as ANN but with addition of controlling the process while satisfying a set of constraints.

Many studies reported on the removal of ammonia/ammonium from water/wastewater. They also have reported on several process control strategies applied in WWTP and WTP. However, few papers to our knowledge reviewing on the implementation of an ammonia treatment method with a process control system in a WTP or WWTP as most of the reviews were focusing on the treatment method and process control strategy separately. Therefore, to close this knowledge gap, this paper reviews on the effectiveness of the biological treatment in removing and reducing the concentration of ammonia from contaminated water along with the effectiveness of the process control system in water and wastewater treatment plant.

This paper will enhance the knowledge on the variables that influence the performance of biological treatment in ammonia removal and concentration reduction, the robustness of advanced controller as a predictive model in WTP and WWTP and how the hybridisation of a PID controller can obtain better results in terms of tuning the parameters of a WTP and WWTP than the basic PID controller.

2.0 Ammonia in water resources

Ammonia is an inorganic compound that is broadly used in various industrial processes. It is often used as a fertiliser and refrigerant. It occurs naturally but sometimes they are also produced by human activities (National Center for Biotechnology Information, 2021). Ammonia is highly soluble in water, and it exists in two forms: non ionised ion (NH_3) and ammonium ion (NH_4^+). The ammonium ion is found to be more abundant in water compared to the non-ionised form (Park et al., 2018). NH_3 is highly toxic to aquatic life and to human health as it is soluble in lipid that enables it to pass through biological membranes easily (Adam et al., 2019). For humans, long-term exposure and ingestion of ammonia compounds may lead to various respiratory problems such as bronchiolitis, laryngitis, pulmonary oedema, tracheobronchitis, and bronchopneumonia (Tonelli & Pham, 2009), lung damage or death. According to the World Health Organization (World Health Organization, 2003), the limit for ammonium concentration in drinking water is 0.5–5 mg/L (European Food Safety Authority (EFSA), 2012). Consuming more than 33.7 mg of ammonium ion per kg of body weight per day can influence the body's metabolism by shifting the acid-base equilibrium, disturbing glucose tolerance, and reducing tissue sensitivity to insulin (World Health Organization, 2003). Excessive presence of ammonia in water can lead to the acceleration of eutrophication process in rivers and lakes. This will cause the depletion of dissolved oxygen, hence creating a toxic environment to the aquatic lives. Naturally, in industrial wastewater, the ammonia content range from 5 to 1000 mg/L and 10 to 200 mg/L in municipal wastewater (Adam et al., 2019). In order to determine the toxicity of ammonia, the pH and temperature must be measured as the ratio of both NH_3 and NH_4^+ in aqueous solution depends on those two variables.

Human body requires more than 70% of water for cells, organs and tissues to function well. Good quality of drinking water is in dire while reserving its resources must be taken care more seriously. Nowadays, water resources are threatened with ammonia pollution because of improper industrialisation management, which, have been reported elsewhere worldwide. According to Verma & Saksena (2010), water pollution at Kalpi (Morar) river and Gomati River in Uttar Pradesh, India was considered extremely polluted, and the water quality exceeded the allowed limits of drinking water standards which was due to rapid urbanisation and industrialisation. According to Hasan et al. (2011), frequent water shortage in certain areas is due to the raw water repeatedly being contaminated with NH_3–N which later cause the shutdown of Malaysian DWTPs.

Nitrogen was a major pollutant in terrestrial ecosystems which was caused by human activities such as fertiliser application, fossil fuel consumption and leguminous crop production, which accelerated nitrogen in the soil, water and atmosphere (He at al., 2011). The degradation of water quality correlated with nitrate leaching from agricultural soils. Juahir et al. (2011) stated that the main sources of river pollution are from sewage disposal, discharges from small- and medium-sized industries and earthwork activities and in different due caused, approximate of five million people had lost their lives due to consuming unsafe water that contains bacterial pathogens (Mwabi et al., 2011).

In a different study, Fu et al. (2012) reported that the presence of ammonia and ammonium ions in water sources originated from human activities in the urban areas, metabolic, agricultural, and industrial processes, and from disinfection with chloramine. In surface water, it was more related towards hydrogeology and climate change. Further study by Dubey & Ujjania, (2013) found out that nearly 70% of surface waters in India had been heavily polluted due to the discharge of domestic sewage and industrial effluents into rivers, streams, as well as lake. Similar study conducted in the water pollution in Haihe River Basin, China was caused by the discharge of industrial and domestic wastewater. It was also revealed that ammonia level in Haihe River was as high as 61,700 tonnes (Wang et al., 2014). Many developed countries, as well as developing countries are suffering from ammonia pollution (refer Table 1). Table 1 presents cases of ammonia pollution worldwide. In countries like China, the ammonia concentration seems to vary according to the seasons. The source of pollution and the concentration of ammonia in each case are shown in Table 1.

As cases of ammonium pollution surge, more stringent enforcement should be imposed. Generally, Water Standard is regulated to ensure highest quality of water. Malaysia has two standards in regulating the quality of raw and treated drinking water. As a comparison, the standard limit for NH_3–N in raw water is below than 1.5 mg/L while for treated water is below than 1.5 mg/L. The European communities, the allowable concentration for NH_3–N is below than 0.5 mg/L. Meanwhile in countries like the USA and Canada, there are no regulated guidelines NH_3–N concentrations in water because the contaminant was found to be low in raw and treated water (Hasan et al., 2011).

3.0 Treatment technologies of ammonia removal in drinking water treatment and wastewater treatment plant

Biological treatment has been widely applied in both municipal and industrial wastewaters, dominantly for pre-denitrification in activated sludge systems (Capodaglio et al., 2015). The application of the biological process is to produce clean and safe drinking water and it is totally dependent on non-pathogenic bacteria that acts as a catalyst for biochemical oxidation. The oxidation process will reduce the pollutants in contaminated drinking water and produce biologically stable water to prevent the growth of microorganisms in the water distribution system (Abu Hasan et al., 2020).

Other than biological treatment, another vast method in treating ammonium in water treatment industry is physicochemical methods such ion exchange, membrane filtration, chemical precipitation, adsorption, air stripping, break-point chlorination and aeration (Karri et al., 2018). Generally physiochemical method offering economically viable treatment facilities with great ammonium removal. However, it is limited to certain qualities of raw water and producing harmful by products such as brine in ion exchange (Adam et al., 2019; Mazloomi & Jalali, 2016), disinfection by product during chlorination

Table 1: Source of ammonia pollution

Cases	Source of pollution	Ammonium concentration(mg/L)	Reference
Malaysia (2011)	Domestic and industrial effluents and sludge discharge	The lowest and highest NH_3–N concentration: • (2007): −0.01 mg/L and 0.7 mg/L • (2009): −0.02 mg/L and 2.27 mg/L	Hasan et al. (2011)
China (2012)	Polluted urban canal	From June to September, 3.89 mg/L	Feng et al. (2012)
China (2018)	Rapid economic development	• Highest during winter (0.82–2.76 mg/L of AN). • Lowest during summer (0.36–0.78mg/L of AN).	Zhang et al. (2018)
Dhaka city (2016)	Domestic, industrial, agricultural, and other wastes	• NH_3–N concentrations in dry season: 34.0–6.35 mg/L • Monthly average of maximum and minimum NH_3–N concentrations: 7.6 mg/L and 0.12 mg/L.	Hossain et al. (2016)

(Charrois & Hrudey, 2007), produces salt precipitation during supercritical water oxidation (Bermejo et al., 2008; Du et al., 2013) etc. The physicochemical and biological methods for ammonia removal in water and wastewater including the removal efficiency, advantages and disadvantages are listed in Table 2.

Table 2: Physicochemical and biological methods from ammonia removal in water and wastewater

Methods	Removal efficiency	Advantages	Disadvantages	References
Ion exchange and adsorption	80–95%	1. Low cost 2. Effective ammonium removal 3. Easy operations 4. Relatively low effluent of total dissolved solids (TDS)	1. Different adsorbent has different capacity 2. Requires brine disposal 3. Effective at certain pH ranges 4. Less reusability	Adam et al. (2019); Mazloomi & Jalali (2016)
Membrane filtration	>95%	1. Ability to produce stable water without the addition of chemicals and consumes low energy 2. Simple and well-arranged process 3. Economically feasible 4. Low production of secondary pollutants and potential recovery and reuse of volatile compounds 5. Adequate for wide range of ammonia concentration, including low concentration (~ 1 mg/L) of ammonia	1. Membranes have the tendency to be fouled 2. Membrane exerts an extra resistance to the mass transfer 3. The lifespan of the membrane varies from short to long, depending on the pore size and effluent handled.	Adam et al. (2019); Karri et al. (2018)
Chemical precipitation	20–30%	1. Moderate cost 2. Reduces sludge production and maintenance cost 3. Valuable slow-release fertiliser	1. High affection by chemical position and presence of other ions 2. Produces new pollutants 3. Requires specific pH and temperature	Adam et al. (2019); Zhang et al. (2011)
Air stripping	50–90%	1. Simple equipment 2. Not sensitive to toxic substances 3. Most commonly used approach for wastewater pre-treatment	1. Requires large stripping tower 2. High time and energy consumption 3. Fouling and scaling on packings 4. Works on specific pH, flow rate and temperature	Adam et al. (2019); Guštin & Marinšek-Logar (2011)
Break-point chlorination	80–95%	1. Adaptable to existing facilities 2. Not sensitive to toxic substances 3. Effective ammonium removal 4. Requires low spaces	1. Requires highly skilled operators 2. Highly sensitive to pH 3. Disinfection of by-products 4. Consumes high chlorine under high organic matter	Adam et al. (2019); Charrois & Hrudey (2007)
Activated carbon	93%	1. Simple design 2. Low initial cost 3. Insensitivity to toxic substances 4. High adsorption capacity and regenerability	1. Depends on pollutants to be removed 2. Becomes a solid waste if not regenerated. 3. Regeneration process can be expensive	Adam et al. (2019); Mook et al. (2012)
Microwave radiation	~ 80%	1. Suitable for high concentration of ammonium 2. Moderate cost	1. Multiple affection such as pH, radiation time, aeration, and initial ammonium concentration 2. Incomprehensive for full scale application 3. Evaporation of NH_3	Adam et al. (2019)
Supercritical water oxidation	>95%	1. Produces molecular nitrogen, water and carbon dioxide 2. Rapid destruction of organic wastes	1. Requires high temperature and pressure 2. High cost 3. Produces salt precipitation 4. Affected by access oxygen and temperature	Adam et al. (2019); Bermejo et al. (2008); Du et al. (2013)
Biological treatment	70–95%	1. Effective ammonium removal 2. Most commonly used approach	1. High energy requirement 2. High cost 3. Sensitive to temperature and climate 4. High risk subsequent processes 5. High ammonium concentration residue 6. Not recommended to remove ammonia with concentration above 300 mg/L	Adam et al. (2019; Bernet et al. (2000); Feng et al. (2012); Karri et al. (2018)

Biological treatment mostly co-integrated with other method to enhance removal capabilities and overcome its deficiency. Early application of biological technology has evolved from using separated reactors for nitrification and denitrification process to single reactor both in anoxic and aerobic environment. Sequencing batch reactor (SBR) later gained attention from researchers for its simplicity in design and remarkably nitrogen removal with excellent sludge settling capacity (Bernet & Sperandio, 2009). Wastewater treatment plant common adopted anaerobic ammonium oxidation (anammox) to remove ammonia. Anammox process applied in reactor with different arrangement such as closed sponge-bed trickling filter with high ammonia removal 82–84% (Sánchez et al., 2015). Mattson et al. (2018) studied the implementation of submerged attached growth reactors for cold-weather ammonia removal where high ammonia removal was observed. Most of these treatment systems showed limited allowable nitrogen loading rates, thus they were principally directed to remove nitrogen from low-strength wastewaters (Chan-Pacheco et al., 2021).

Recent study lingered on the possibilities of combining annamox process with alternative electron acceptors such as sulphur, ferric iron, and anodes in microbial cells (anodic anammox) (Chan-Pacheco et al., 2021). Zhu et al., (2022) conducted a study of anaerobic ammonium removal with Fe (III) (feammox) reduction in the up-flow sludge blanket reactor. The ammonium removal was attributed to the carbon sources and ammonium acts as electron donors for Fe (III) reduction. Ammonium removal improve significantly whilst energy cost for ammonium removal could significantly decrease by addition of Fe_2O_3. Sulfammox is applied in more specific environment where high ammonia and sulfate content which sulfate (SO_4^{2-}) used as an electron acceptor under anaerobic conditions for ammonium removal. It was studied in various system such as suspended growth, biofilm, granular and hybrid reactors (Dominica et al., 2021).

Table 3 shows different types of biological ammonia treatment technologies being applied in WWTP and WTP. It was found that researchers were focusing more on biological treatment compared to

Table 3: Biological treatment of ammonia in DWTP and WWTP

Application	Technologies	Percent removal, %	Reference
DWTP	GAC-sand dual media filter	35.2%	Feng et al., 2012
DWTP	Biological aerated filter (BAF)	75.3%	Han et al., 2013
DWTP	Slow sand biofilter (BioSSF)	98.3%	Hasan et al., 2019
DWTP	Sand biofilter	96–98%	Subari et al., 2018
GWTP	Biofilter	90.82%	Cheng et al., 2017
Municipal Waste Treatment	Ion exchange with various commercial minerals	Ammonium ions: 55.7%	Seruga et al., 2019
Water purification system	Bio-sand method & Sponge layer filtration method	Bio-sand filtration: 76.342% Sponge layer filtration: 80.768%	Homagai & Poudel, 2018
WTP	Duckweed	78 – 98%	Hossain et al., 2016
WTP	Copolymerization air flotation-carbon sand filtration process	Ammonia nitrogen: 27.5%	Wang et al., 2018
WTP	Biofilter	pH 6: 13% pH 7.5: 48% pH 9–10: >90%	Hamidi et al., 2020
WWTP	Air stripping	Semi-batch conditions (100%) Batch conditions (96.7%)	Ozyonar et al., 2012
WWTP	Moving bed biofilm reactor (MBBR)	>90%	Shore et al., 2012
WWTP	Methane- and methanol-dependent bacterial consortium (methanotrophs and *Methylophilus*)	58.9%	Kim et al., 2020
WWTP	Air stripping	94.2%	Ata et al., 2017

physicochemical treatment as biological treatment operates at low cost and involves less maintenance of the equipment. Furthermore, biological treatment has shown to be efficient in treating ammonia for both wastewater and drinking water. By referring to Table 3, it can be observed that the removal efficiency of the biological treatment's ranges from 35 – 98%. This shows that biological treatment is preferable in treating ammonia to produce good quality effluent. It is a fact that biological treatment can reduce the concentration of ammonia in both WTP and WWTP. However, WWTP focuses on using physicochemical methods to treat ammonia as shown in Table 3. In most cases, WWTP uses biosand filter for pathogens removal and to reduce the levels of COD and BOD in wastewater as reported by Mulugeta et al. (2020) and Primasari et al. (2020).

Biological treatment mostly conducted in biosand filtration (BSF) in removing ammonia in order to supply clean drinking water for the community in WTP. Biosand filter (BSF) is an innovation biological treatment adapted from the traditional slow sand filter (SSF) used widely in developing countries to gain access to clean drinking water. It is modified in a way that the BSF is intermittently operated so that the user can control the amount of water filtered (Ahammed & Davra, 2011; Kennedy et al., 2012). A *schmutzdecke* layer is formed in order to provide effective filtration in treating raw water. It is usually embedded between the sand grains at the top of the filter. The *schmutzdecke* serves as a biofilm that assist in the removal of pathogens or contaminants in the raw water. Fig. 3 illustrates a schematic diagram of a BSF.

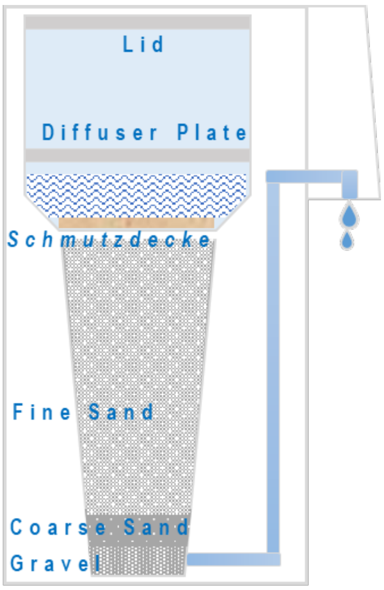

Fig. 3: Cement biosand filter

BSF is able to reduce turbidity, chemical oxygen demand, colour, suspended solids (Hasan et al., 2019), pathogens, and contaminants from dirty water (Hasan et al., 2019; Suprihatin et al., 2017). Many case studies have proven that the use of BSF in treating contaminated water managed to achieve maximum removal percentage of nitrate, nitrite, ammonium, manganese, ammonia-nitrogen, total suspended solids (TSS), organic matters, heavy metals, total organic carbon (TOC) and pathogens, where the quality of the treated effluent meet the WHO quality standards for drinking water and also with respect to each country's water quality standards and regulations. In addition, the BSF showed high capability of improving turbidity of the treated water. Baraee et al. (2016) and Suprihatin et al. (2017), found out that the BSF and GAC-sand biofilter are capable in reducing the turbidity of the polluted water with removal efficiency between 40.3% to 89.36%.

Some of the variables that have an influence towards the performance of the BSF are the hydraulic loading rate (HLR), hydraulic retention time (HRT), temperature, contaminant concentration, filtration rates and alkalinity. The rates of reactions in converting ammonia to NO_2–N and NO_3–N are influenced by the hydraulic flow characteristics of the filter. It was found that operating a GAC-sand biofilter under low HLR resulted in a more efficient performance (Baraee et al., 2016). However, an increase in the HLR may cause a reduction in empty bed contact time (EBCT). EBCT plays an important role in providing a degree of contact between the filter media and the water flowing through the filter, allowing the organic particles to be adsorbed and removed from the filter. Further research was recommended in order to obtain the precise HLR and GAC media depth to increase the EBCT which can help in sustaining a longer operation of high-quality effluent production. Ammonium removal also correlates with hydraulic retention time (HRT). The HRT is the average time that a compound remains in a treatment tank or unit. The longer the retention time, the higher the removal efficiency of ammonium (Suprihatin et al., 2017).

The biofilm layer is developed by the accumulation of microorganisms at the surface of the biofilter. It plays a major role in the biodegradation bacterial kinetics. The development of the biofilm layer is dependent on temperature and substrate. Ammonium removal rates is highly influenced by the formation of the biomass in the BSF, and the biofilm growth is influenced by temperature. The bacteria that are attached on the biofilm are used for nitrogen removal as they would increase biomass retention time for reliable nitrification. It has been reported that the efficiency of nitrification process would decrease if the temperature of the influent is low (Saidu, 2009). Therefore, many case studies have reported in obtaining optimum temperature and pH for efficient ammonium removal, which is within the range of 15 to 35 °C (Liu et al., 2020) and a pH of 7–9 (Sajuni et al., 2010).

Nitrification is the process of ammonia being oxidized to nitrite by ammonia oxidising bacteria (AOB) or ammonia oxidising archae (AOA) and subsequently convert nitrite to nitrate by nitrite oxidising bacteria (NOB) under aerobic conditions with the help of autotrophic bacteria. The main limiting factor for increasing the nitrification rate and also ammonia removal is the specific surface area of the biofilm (Lysakovskaa, 2015). *Nitrosomonas, Nitrosococcus, Nitrosospira, Nitrosolobus,* and *Nitrosovibrio* represent AOB that converts ammonia to nitrite, while *Nitrobacter, Nitrococcus, Nitrospira*, and *Nitrospina* represent NOB that further oxidise nitrite to nitrate. In most case studies, *Nitrosomonas* and *Nitrobacter* were found to be the dominant AOB and NOB (Jun & Wenfeng, 2009; Leyva-díaz et al., 2015). It is possible for further removal of nitrate to nitrogen gas through anaerobic processes as shown in Table 4. Table 4 depicts main bacterial reaction associated with a biological filter.

Alkalinity also plays a role in influencing the nitrification process (Saidu, 2009). When ammonia is converted to nitrate, this reaction will consume alkalinity in the form of carbonate and bicarbonate. The carbonate and bicarbonate serve as a supplement for nitrifying bacteria. Theoretically, the greater the alkalinity of the influent, the higher the nitrification process. Nevertheless, it is necessary to set a minimum level of carbonate alkalinity to fulfill the requirement of ammonia-oxidiser's inorganic carbon for cellular synthesis and growth (Biesterfeld et al., 2003). A study by Shanahan & Semmens (2015) reported that bicarbonate alkalinity had a strong influence towards the nitrification performance of a membrane aerated bioreactor (MABR) such that the nitrification performance increased from 65 to 77% as the concentration of bicarbonate increased from 0.6 to 4.8 mM. A trend of ammonia-nitrogen concentration being directly proportional to the level of alkalinity was observed by Campos et al. (2013). With that being said, concentration of ammonia-nitrogen will decrease if alkalinity is decreased. Since alkalinity encourages bacterial growth, therefore, both pH and alkalinity need to be balanced in order to promote optimal conditions for the bacteria to convert ammonia to nitrite.

Continuous studies have been conducted to improve the performance of the BSF and the drinking water quality. One of them is by introducing iron oxide-coated sand in the BSF. The iron oxide-coated sand is an innovation that is used to remove heavy metal ions from water. Introducing iron oxide-coated sand during

Table 4: Main bacterial reaction associated with a biological filter

Process	**Reaction**	**Microorganism**		**References**
		Freshwater	**Marine**	
<u>Nitrification</u> Ammonium oxidation	$NH_4^+ + 1.5O_2 \rightarrow NO_2^- + 2H^+ + H_2O$	*Nitrosomonas oligotropha*	*Nitrosomonas* sp. *Nitrosomonas cryotolerans* *Ntrosomonas europaea* *Nitrosomonas cinnybus/nitrosa* *Nitrosococcus mobilis*	Timmons & Ebeling, 2010
Nitrite oxidation	$NO_2^- + H_2O \rightarrow NO_3^- + 2H^+ + 2e^-$	*Nitrospira* spp. *Nitrospira marina* *Nitrospira moscoviensis*	*Nitrospira marina Nitrospira moscoviensis*	Timmons & Ebeling, 2010
<u>Denitrification</u> Autotrophic (sulfide-dependent)	$S_2^- + 1.6NO_3^- + 1.6H^+ \rightarrow SO_4^{2-} + 0.8N_2(g) + 0.8H_2O$		*Thiomicrosporia denitrificans* *Thiothrix disciformis Rhodobacter litoralis* *Hydrogenophaga* sp.	Timmons & Ebeling, 2010
Heterotrophic	$5CH_3COO^- + 8NO_3^- + 3H^+ \rightarrow 10HCO_3^- + 4H_2O$	*Pseudomonas* sp. *Comamonas* sp.	*Pseudomonas fluorescens* *Pseudomonas stutzeri Pseudomonas* sp. *Paracoccus denitrificans*	Timmons & Ebeling, 2010

the maturation period and after cleaning operation resulted in a better performance of BSF (Ahammed & Davra, 2011). Constructed wetlands are artificial cost-effective wastewater treatment system that have been designed and engineered to mimic and improve natural wetlands in treating municipal or industrial wastewater, greywater, or stormwater run-off. Polluted rivers can also be rehabilitated by constructed wetlands. Therefore, combining the two systems would be beneficial in improving water quality. As reported by Mtavangu et al., (2017), integrating constructed wetland with bio-sand filters resulted in higher feasibility for treating high turbid water for drinking. Lastly using brick chips layer in BSF. BSF with brick chips layer managed to remove ammonia more efficiently compared to BSF with charcoal layer (Kabir et al., 2020).

4.0 Model prediction of ammonium removal in water treatment and wastewater treatment plant.

Model prediction of biological process known to be tedious which requires a lot of collection of empirical data. However, in line with technological advancement, many studies were conducted with the use of computational aided software.

The fundamental of dynamic models is that it plays a major part in process dynamics and control, in a way that it can be used to:

- Improve understanding of the process
- Train plant operating personnel
- Develop a control strategy for the process
- Optimise process operating conditions

The key objective of a process control is to ensure that the key process-operating parameters are kept within the reference value or setpoint. Process modelling enables a deeper understanding of the tests and outcomes, setting a strong start to the optimisation process, and making it possible and easier to visualise where the bottlenecks are and what are the inefficiencies.

Artificial neural network (ANN) has been applied in the water technology field to predict water quality, average level of contaminants in river and performance of filters used in the treatment plant. ANN is an artificial intelligence designed to carry out similar function of the human brain to analyse, processes information and making decisions in a humanlike manner. It consists of basic computing elements that interconnect to one another, in which it replicates the way neurons behave. The ANN relates both input and output variables. ANN is widely used for nonlinear systems for complex processes because the model could express nonlinear and complicated patterns and problems with the developed algorithms. As stated by Fan et al. (2016), their wide range of applicability and ability to solve complex and nonlinear relationships between the variables without underlying mechanism had made them became widely known in the engineering sector.

ANN is a predictive model that replicates how the human brain works. It has the ability to self-learn and is not restricted to the input variables provided to them. These network models are capable in adapting to any situations just by learning from an example of a system or from historical data. Khataee & Kasiri (2011) stressed that the ANN modeling does not require any additional information regarding on the mechanism and kinetics of biodegradation of treated contaminants for biological water and wastewater treatment processes. Many researchers have highlighted how the simulation of artificial neural network in process control system has been proven to be quite beneficial in predicting the performance of WTPs and WWTPS accurately. Since WTPs and WWTPs kept data from many years back, these data were used as an input for the ANN model to simulate predictions of the desired parameters. Most of the predicted data was almost similar to the experimental values (Kundu et al., 2014; Pakrou et al., 2015; Tümer & Edebali, 2015). Not only that, but it is also able to predict effluent violations, the behaviour of a system, water production variations, removal efficiency, and water quality of the effluent of the WTPs and WWTPs, and rivers.

ANN is capable in detecting the limit violations of the effluent in ammonia removal studies. Since ammonia has been one of the major pollutants in rivers, producing effluent with concentration that is within standard regulations is crucial for WTPs and WWTPs. Hence, the implementation of ANN in both treatment plants is used to predict the effluent pollutants concentration. Huang et al. (2017) used near-infrared spectroscopy with back-propagation neural network in predicting the concentrations of total nitrogen, ammonia nitrogen, and nitrite nitrogen, which then allows monitoring polluted rivers more convenient. ANN is also used in determining key parameters that have big influence towards the calculation of approximation algorithm. Ofman & Sokolowska(2019) developed a neural network model that allowed accurate representation of changes in trend of individual forms of nitrogen in both anaerobic and aerobic phases inside a granular sludge batch reactor (GSBR). It seems like the ANN model was able to show which parameter has the greatest influence on calculation accuracy and is responsible for selected pollutant removal. It is worth noting that using larger number of variables increase the difficulty in identifying the key variables that have significant impact on changes during wastewater treatment.

Neural network is comprised of three layers; input, hidden and output. Fig. 4 illustrates the structure of an artificial neural network (ANN). The key component of the ANN to perform better as a predictive model would be the hidden layer. The hidden layer has complex functions that create predictors. Generally, many researchers claimed that using more than one hidden layer in a multi-layer feed-forward network is unnecessary. Instead, changing the number of hidden nodes in one hidden layer is enough in producing different results (El-Din & Smith, 2002). By following the rule-of-thumb, calculating the correct number of neurons to be used in a hidden layer can be achieved as follows (Ganatra & Panchal, 2011):

- The size of hidden neurons should be between the size of input layer and output layer.
- The number of hidden neurons is 2/3 (or 70% – 90%) of the size of the input layer. If it is insufficient, number of output layer neurons can be added later on.
- The number of hidden neurons should be less than twice the number of neurons in input layer.

Increasing the number of hidden layers can make the neural network to solve more complex problems. Karsoliya (2012) reported that one or two hidden layers are sufficient in solving non-linear complex problem. However, it will affect the duration of the neural network to produce the output. Nevertheless, neural network model with two hidden layers performed better when handling complex data sets compared to neural network model with one hidden layer (Qiu et al. (2016). The ANN model with minimum errors is often chosen as the best model. Güçlü & Dursun (2010) had changed the number of neurons in the hidden layer between 3 and 100. It was found that the best suited model of ANN for COD, SS, and MLSS was 8:20:1, 8:23:1 and 8:14:1 respectively which corresponds to the node number of inputs, hidden and output layers.

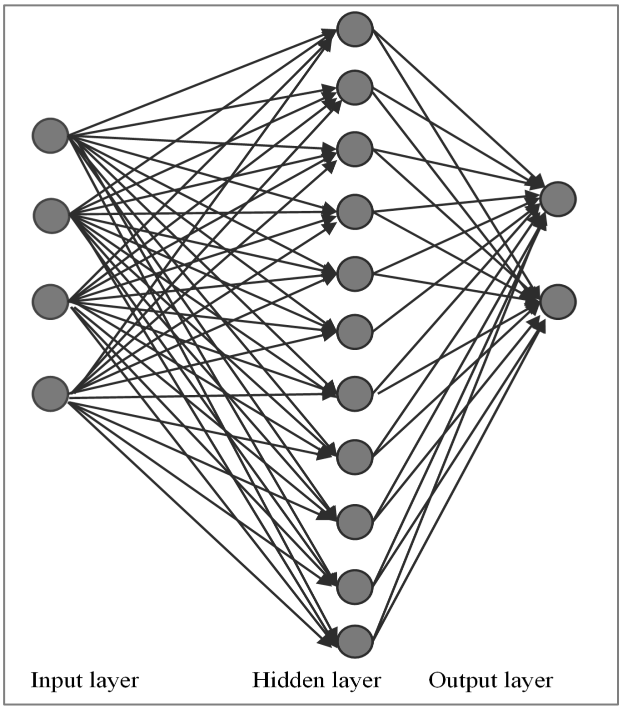

Fig. 4: Structure of artificial neural network layers

This proves that the ANN with the highest number of hidden neurons will not guarantee as the best model. In order to determine whether the constructed ANN model performed efficiently, the model is evaluated using statistical techniques, which are the mean squared errors (MSE), and correlation coefficient (R^2). ANN structure with the highest correlation coefficient and lowest mean squared error is chosen as the best performing model.

In addition, increasing the number of hidden nodes in the hidden layer will also affect the network in terms of memorizing the training data sets instead of focusing on the important features (El-Din & Smith, 2002). Based on previous research, it is recommended that both number of hidden layers and number of neurons in each of the hidden layers should be taken into consideration. Table 5 compiled the model prediction using ANN by various researchers.

5.0 Control strategy of ammonia removal in wastewater treatment and water treatment plant.

Many studies have been conducted on designing a control system that is suitable for WTPs and WWTPs. The use of a conventional PID controller is very common in industrial feedback control loops due to its robust performance in a wide range of operating conditions. The controller is mainly used in the chemical industry to regulate temperature, flow, pressure, speed, and other process variables. However, the simplicity of the traditional PID controller makes it less reliable when dealing with complex system. Two of the popular tuning methods are Ziegler Nichols (ZN) and Cohen-Coon (CC). Both methods have been proven to be simple and easy in tuning PID gains. In addition, the ZN tuning method is best for step test and load disturbance test, whereas CC tuning method only performs better at set point change. The nature of ammonia removal is non-linear. Nevertheless, researchers have found it to be deficient in nonlinear systems (Azman et al., 2017). Table 6 shows a comparison of results obtained from previous case studies on the optimisation of a PID controller.

A conventional PID controller is often enhanced with other tuning methods or algorithms to develop the best control system in the water technology fields. A hybrid duo of conventional and advanced control system has improved in many ways resulting improved and better control strategy. Honga et al. (2012) found that the standard deviation of an output chlorine rate using artificial neuro-fuzzy inference system combined with PID controller system was 3.6 and 7 times less than the traditional PID controller system. Sabri & Al-Mshat (2015) compared the control performance of water level in a tank using conventional PID controller and a fuzzy logic controller (FLC). It was observed that the FLC showed better enhancement of control strategy in terms of no overshoot, faster settling time, better set point tracking and produced lower integral of time and absolute error (ITAE), integral of time and squared error (ITSE), integral absolute error (IAE), and integral squared error (ISE). Based on Table 6, it shows that optimisation of a basic PID controller with another control strategy can improve the step response.

In recent years, many researchers have implemented a meta-heuristic optimisation technology in the control system of water and wastewater treatment. Some of the popular meta-heuristic optimisation technologies are the gravitational search algorithm (GSA), particle swarm optimisation (PSO), and grey wolf optimisation (GWO). PSO-PID controller was stated to show better performance over traditional PID controller in terms of improved step response such as reduced steady state error, fast rise

Table 5: Model Prediction using ANN

Model	Findings	References
Elementary artificial neural network with multiple linear regression (MLR)	Both models produced accurate model however some ANN models resulted in larger deviation between model and validation data.	Kok et al. (2019)
Artificial neural network (ANN)	ANN could simulate the trend of ammonium and phosphate in steady streams however incapable in extreme events due to complexity of the transport of those chemicals.	Sedaghatdoost (2020)
Multilayer perceptron (MLP) artificial neural network (ANN) and Response surface methodology (RSM)	MLP-based prediction tool produces better predictions than RSM with better scatter plot of actual and predictions value, and highest regression coefficient (closed to 1).	Temel et al. (2021)
Feed forward back -propagation ANN.	The performance of batch reactor for the treatment of slaughterhouse wastewater were modelled using ANN and the performance were evaluated based on mean square error function and regression analysis. Both analyses show great accuracy.	Kundu et al. (2014)
Artificial neural network (ANN)	ANN used for optimization of nitrogen elimination from wastewater using annamox bacteria in fixed-bed reactor. Better R^2 and MSE value resulted in the study.	Mojiri et al. (2020)
Artificial neural network (ANN)	Developed neural network model showed better R^2 with maximum removal in municipal wastewater treatment plant.	Pakrou et al. (2015)
Artificial neural network (ANN)	The model developed in this work has satisfactory result and accuracy. The neural network modeling effectively predicts the performance of wastewater treatment plant.	Tümer & Edebali (2015)
Artificial neural network (ANN) with multilayer perceptron (MLP), learned using the Broyden-Fletcher-Goldfarb-Shanno algorithm.	Developed ANN models indicated variables the most influencing of particular nitrogen forms in aerobic and anaerobic phase of GSBR reactor. ANN models can be used in further studies on modeling of nitrogen forms in anaerobic and aerobic phase of GSBR reactors.	Ofman & Sokolowska (2019)
Artificial neural network (ANN)	The results indicate that the proposed soft sensor based on a deep-structure neural network in wastewater treatment plant can achieve better prediction and generalization performance in comparison with commonly used methodologies.	Qiu et al. (2016)

time and quick settling time in the application of level control in conical tank-based wastewater treatment plant (Mercy & Girirajkumar, 2017). In another development, it has been observed that the GSA-PID controller showed better results in terms of transient response by 20% - 30% compared to PSO-PID controller. Recently, in 2018, it found that, the GWO based controller showed better efficiency and suitability over other algorithms such as the artificial bee colony (ABC) algorithm, differential evolution (DE) algorithm, and PSO algorithm in tuning the controller parameters in a RO water treatment plant (Rathore et al. 2018).

The advanced process control that is often used in the WTP and WWTP is the model predictive control (MPC). MPC is an advanced control method that has been widely used in industrial control applications, where its algorithm is based on a predictive model of the process. The model is applied in most industrial applications for its ability in predicting future control actions and control trajectories (Kumar & Anwar, 2012). MPC requires a mathematical model of a process, whether the mathematical models being linear models, reduced nonlinear models or neural networks to obtain the control signal by minimizing an objective function. Reduced nonlinear models seem to provide

Table 6: Control strategy in water and wastewater treatment plant

Control strategy	**Manipulated variables**	**Result**	**Reference**
PID-MPC	Temperature	No overshoot	Rajasekaran & Kannadasan (2013)
GSA-PID	Substrate and DO concentration	Rise time, 0.51s Settling time, 4.91s Overshoot, 2.10%	Aziz et al. (2015)
PSO-PID		Rise time, 0.76s Settling time, 5.78s Overshoot, 7.29%	
PSO-PID	Level	Delay time, 18.34 s Rise time, 29.76 s Settling time, 81.54 s ITAE, 0.0134 IAE, 178.76 MSE, 1.235 ISE, 146.87	Mercy & Girirajkumar (2017)
Astrom and Hagglund		Delay time, 16.23 s Rise time, 24.56 s Settling time, 84.45 s ITAE, 32.46 IAE, 143.83 MSE, 78.12 ISE, 124.53	
PID	Level	Overshoot, 11.2% Settling time, 250 s Rise time, 34 s	Sabri & AL-Mshat (2015)
Fuzzy		No overshoot Settling time, 105 s Rise time, 29 s	
GWO-PID	Permeate flux and conductivity	1. Flux loop Rise time: 0.4079 s Settling time: 0.5410 s Overshoot: 0.0247% 2. Conductivity loop Rise time: 1.0716 s Settling time: 2.4746 s Overshoot: 0%	Rathore et al. (2018)
PSO-PID		1. Flux loop Rise time, 0.1953 s Settling time, 0.6696 s Overshoot, 3.0501% 2. Conductivity loop Rise time, 1.3302 s Settling time, 11.1810 s Overshoot, 18.3052%	

better prediction capability than a linear model.

MPC has been proven to show satisfactory tracking and disturbance rejection performance of a WTP and WWTP in terms of ammonia removal, reduction in ammonia and nitrate concentrations in the effluent, improve effluent quality and reduce energy, as well as operation consumption costs. In most previous studies, many supported that MPC system is superior to conventional PID controller. However, Vrečko et al. (2011) debated that ammonia feedforward-PI controller displayed better results compared to ammonia MPC. Nevertheless, Kumar & Anwar (2012) concluded that neural-based controller can achieve tighter regulatory control compared to single-loop controllers that use multivariable feedforward-feedback model predictive control.

Based on recent studies, it seems that the solution to overcome the weakness of the PID controller is by optimising it with other control algorithm in order to gain ideal control of the nonlinearity of ammonia removal in water treatment facilities. Nevertheless, MPC has also shown great capability in handling complicated, nonlinear control processes in regulating ammonia concentration of the effluent.

6.0 Conclusions

Rapid urbanisation and industrialisation are the roots cause of ammonia pollution where ubiquitous toxic substances polluted main source of raw water supplied. Biological treatment offers better alternative of conventional physical chemical treatment of ammonium removal. It is showed by many developed countries has applied the technology in their water treatment facility. Biological treatment adopted simple mechanism and environmentally friendly solution to treat ammonia. It is capable in removing ammonia and produce high quality water within the standard limit when optimum operating conditions are met. As technologies have evolved, tuning the water parameters such as pH and turbidity level on a monitoring device is very convenient as it allows us to place a setpoint according to required range. Furthermore, to be able to predict the outcomes of the biological treatment would bring much advantage where overall performance could be predicted as well as detecting effluent violations. Artificial neural network (ANN) is a promising computing system that is able to enhance the overall performance of WTP and WWTP. A conventional PID controller alone is not suffice in tuning the parameters or obtain the ideal control effect in a WTP and WWTP due to their nonlinear dynamic behaviour, time varying parameter values, limitation on the manipulated variables, correlation between the manipulated and the controlled variables, unconsidered and frequent disturbances, delay on input and measurements. A mathematical relationship between the input and output of the system should be known to formulate the controller. The efficiency of a PID controller improved tremendously when hybridisation implied with certain tuning methods such as Ziegler-Nichols (ZN) or Cohen-Coon (CC), fuzzy control system, or with a metaheuristic method such as the particle swarm optimisation (PSO), gravitational search algorithm (GSA) and grey wolf optimisation (GWO). For future prospects, further study on both ammonia treatment methods together with process control systems in overcoming river pollution that has been a major crisis all over the world.

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