Metaheuristic Optimization of Ammonia Factor as a Eutrophication Pollution Emission Descriptor for Trophic State Stability

Ronnie S. Concepcion II, Sandy C. Lauguico, Argel A. Bandala, Jonnel D. Alejandrino, Elmer P. Dadios, and Edwin Sybingco

Abstract—**Aquaponic toxicity relies on the combinations of its pollution parameters that are dissolved in water and emitted in air. Ammonia is considered as an important indicator affecting aquaculture species, water nutrient imbalance and air pollution. Trophic state of aquatic body is measured by ammonia. In this study, the suitability of metaheuristic models, namely, genetic algorithm, simulated annealing, water cycle algorithm, enhanced vibrating particles system and particle swarm optimization, in determining the optimum condition of ammonia factor for providing minimal toxicity and oligotrophication was determined by varying its corresponding hyperparameters. The parameters that were optimized are water temperature and pH level. These parameters significantly affect ammonia factor that is an essential contributor to eutrophication. The optimized genetic algorithm yielded the practical-ideal fitness function value for ammonia factor as to compare with other optimized metaheuristics based on optimizing time. It selected the 50 fittest individuals based on their fitness score with the rate of 0.2 and proceeds to recombination process to extract characteristics from parent chromosomes with crossover rate of 0.8. The mutation rate of 0.01 was injected to form diversity and to test if the global solution was attained. The tournament size is 4 and the reproduction elite count is 2.5. The best condition of the ammonia factor was extracted when the number of generations has been reached. The GA results showed that the optimum condition for ammonia factor that will prevent eutrophication and provide ecological balance in aquaponic system needs a temperature of 29.254 °C and pH of 7.614.**

Index Terms—**Ammonia factor, eutrophication, metaheuristic, optimization, swarm intelligence.**

I. Introduction

Eutrophication is one of the environmental impact categories indicating the increase amount of nutrients in the water surface. According to the Organization for Economic Cooperation and Development (OECD), it naturally results to excessive algae development that leads to anoxia, low natural light intensity on the ground level and high ammonia concentration. The Asian region is affected with eutrophication by 54%. Lakes are the most vulnerable aquatic area that is being affected by this water quality deterioration, though, fishponds are not exempted to this phenomenon. Eutrophication is mainly due to severe concentration of marine animal excretions, decaying biomass such as dead fish and unoxygenated algae, and fertilizer that are not properly disposed and recirculated in the system. Inhibited nitrogen cycle significantly yields eutrophication. It can lead to aquatic toxicity if not properly regulated.

Ammonia is the simplest pnictogen hydride with chemical formula of NH_3. It is an important player in any aquaponic system. Higher amount of gaseous ammonia irritates the concentration of a balanced system. It can be corrosive when dissolved in water with 10% to 25% concentration. It becomes dangerous for the environment when the concentration is above 25%. But ammonia is non-toxic in low level and provides proper nutrients to plants. Still, ammonia is considered as one of the pollution emission parameters of eutrophication aside from phosphorus (P), orthophosphate, total nitrogen (N), nitrogen in nitrate, dissolved oxygen, water transparency and chlorophyll-a (Chl-a). Certainly, there is a need to analyze ammonia effects both to the environment, and plant and marine animal being cultivated. The normal method of measuring ammonia level is through laboratory facility which tends to delay the assessment of an aquatic area. Various studies to determine and assess ammonia factor as were performed from the past and are presented hereunder.

The interaction of nitrite, unionized ammonia, copper, aluminum and zinc to level up toxicity was evaluated and predicted using two classical models, namely, concentration addition (CA) and independent action (IA) models. The generalized concentration addition (GCA) model was able to predict the toxicity details in any mixture [1]. A method of predicting the ammonia nitrogen level of was done using radial basis function neural network (RBFNN). The developed neural network is convenient as it can predict ammonia-nitrogen through the second correction. A real-time and on-line monitoring was done to compensate the delay measurement of ammonia test samples in the laboratory [2]. A knowledge-based real time monitoring system was done using ammonia sensor tandem with internet of things (IOT). The balance of water quality was preserved by monitoring water quality parameters such as dissolved oxygen, ammonia, pH, temperature, salt, carbonates, bicarbonates, nitrates and sour gas. Based on the study, the threshold range they

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employed for ammonia is 0 to 0.1 ppm for positive impact in the biotic system [1]. The water quality parameters of pH, temperature, dissolved oxygen and ammonia factor were regulated using Arduino Mega 2560 for tilapia farming. This experiment was done to augment the significant effects of feeding to specific water quality parameters [2]. A technique of ammonia measurement was done using test strips and camera. The ammonia test strip was submerged into the pond water for fifteen minutes and upon the stable change of color on the test strip, it will be then checked by the camera based on the stored standards on the database. The level of ammonia is expressed based on the standard ammonia color value table. It is a simple way of measuring ammonia dissolved in water and an effective method to assess the suitability of the breeding pond [3]. The effect of water salinity on the rate and concentration of excreted ammonia from a marine species called meretrix, a class of edible clam, was conducted to understand if water quality in return affects the ammonia production of aquaculture animals. The study concluded that the atomic ratio of consumed oxygen and excreted ammonia defines the metabolizing sources of energy of marine animals. Ammonia sensors were used to monitor the excreted ammonia level [4]. An estimation technique for ammonia nitrogen in aquaculture was done using support vector machine (SVM). The soft sensing model was constructed using 230 valid data samples of temperature, pH, conductivity, dissolved oxygen and ammonia. Ammonia sensor deployed in turbot aquaculture served as the data acquisition set for the system, making partial least SVM a suitable soft sensing model in approximating ammonia nitrogen level [5]. An optimization of ammonia concentration in pinctada martensii, a type of pearl oysters, was done using simultaneous variation of water salinity and temperature levels. The Box-Behnken design and response surface method as technically employed in the system to analyze and create an optimization model. The study was able to determine that the combined effect of temperature and salinity must be accounted to balance the ammonia level [6].

Despite of the abovementioned technologies and methodologies that have been implemented to monitor and predict the ammonia concentration, there are no studies as of this writing that is focus on optimizing ammonia factor of an aquaponic system that cultivates carp and tilapia in aquaculture chamber and lettuce in the hydroponic chamber.

This study aims to determine the suitability of metaheuristic algorithms namely, genetic algorithm (GA), water cycle algorithm (WCA), enhanced vibrating particles system (EVPS), simulated annealing (SA) and particle swarm optimization (PSO) in finding the optimum condition of ammonia factor for providing minimal toxicity impact in the ecological system of aquaponics. Water temperature and pH parameters are the affecting physical variables intended to be optimized as these two are strong predictors. Enough knowledge on the ambivalent combinatory effects of these two parameters will lead the agricultural sector to further understand ammonia factor as essential parameter for eutrophication. Metaheuristic models were chosen it usually yields realistic optimized values in suitable time. The data from water samples were collected from an artificial pond in

the Rizal, Philippines with tilapia and carps as cultivars.

II. Ammonia Factor

The biogeochemical process of converting nitrogen into different chemical forms that that happens in aquatic, terrestrial and atmospheric ecosystems is called nitrogen cycle. This natural cyclic process that is primarily moved by microbes constitutes important chemical processes namely, nitrogen fixation, ammonification, nitrification and denitrification. Nitrogen fixation is the conversion of atmospherically abundant nitrogen into nitrites and nitrates. Plants intake nitrates as their food. Organic nitrogen is the initial result of fish effluents and decaying biomass that includes dead fishes. Through ammonification, it converts the organic nitrogen to ammonium. And ammonium is converted to nitrate in nitrification. With this ideal nitrogen cycle, plants will not be deprived of from their foods and fishes will not be toxified. But ammonia gas alone with high concentration is a toxic to plant and fishes [7]. Discrete amount of ammonia must be present in the system in order not to toxify the plant being cultivated and will not contribute to the development of eutrophication. The characteristic of ammonia conversion in a recirculating aquaculture system states that nitrification and aerobic denitrification is achievable in aerobic and low chemical oxygen demand (COD) conditions only [8]. The nitrification performance was monitored by [9], [10] and [11].

Ammonia factor (A) is a unitless indicator that defines the concentration of a water system based on ammonia level. It is analogous to the layman term ammonia. Chemically, ammonia dissolved in water yields ammonium (NH_4) and hydroxide (OH^-) as shown in the ammonification process in (1). Ammonium decreases the pH level. The unionized ammonia is more toxic than ammonium because it is a soluble gas that has no charge. The biological cells of fish cannot properly consume ammonia. On the other hand, nitrogen in the form of nitrate (NO_3^-) is responsible for the foliage development of plants. It is derived from animal manure and fertilizers. Depravity of control will yield to eutrophication.

$$NH_3 + H_2O \leftrightarrow NH_4^+ + OH^- \tag{1}$$
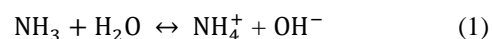
Ammonia factor is computed based on pH and temperature levels using (2) [12]. The constant α is equal to 0.0901821, β is 2729.92, and γ is 273.15. Ammonia factor is indirectly controlled by temperature in degree Celsius, T, and pH level, P [2]. In this study, ammonia factor is studied in terms of temperature and pH level.

$$A = [10^{\alpha + \left(\frac{\beta}{\gamma - T}\right) - P} + 1]^{-1} \tag{2}$$

A. Temperature

Temperature is a scientific measure of the average kinetic energy of particles in a particular matter. It determines the rate of chemical reactions. The instantaneous temperature, T, is related with quantum yield Φ that is mathematically defined in (3) [13]. Quantum yield is a photosynthetic parameter based on natural and artificial radiation process that describes the frequency of an event such as chemical

reaction per photon being absorbed by the system. As temperature increases, the quantum yield decreases. Equation 4 mathematically defines the relationship of the number of photons emitted, α, and the number of photons absorbed, β, with proportionality constant, k.

$$\Phi = 0.0843 - 0.0003T - 0.0000341T^2 \tag{3}$$

$$\Phi = k\frac{\alpha}{\beta} \tag{4}$$

Water temperature is considered as the abiotic master factor due to its significant effects to aquatic system, particularly to organisms. Thus, it is an important factor in assessing water quality. Temperature is accounted for numerous effects such as varying metabolic rates of and photosynthetic rate in aquatic system, toxicity, level of dissolved oxygen and gas concentrations, electrical conductivity, pH and water density. Both fishes and aquatic plants are restricted with temperature variance. Most of these species prefer warmer water temperature that promotes metabolism, but it does result to stronger photosynthetic activity for algae. The formation of algae above the water surface results to decrease of dissolved oxygen and low light intensity reaching the middle layer and bottom of the body of water, thus, introducing nutrient imbalance in aquatic system. But there are certain temperature range that inhibits this fast-photosynthetic rate to happen. It normally occurs for temperatures below 21°C and above 35°C [14]. As temperature increases, the dissolved oxygen decreases. It increases the solubility in the system. It is responsible in drifting ammonia and ammonium conversion in water. Likewise, pH generally decreases as temperature increases.

Water temperature is affected by air, sunlight, and sources of thermal pollution. The aquatic body is stratified with epilimnion, metalimnion, hypolimnion and monimolimnion. Thermocline is layer of water that divides it based on temperature levels. It is existing just above metalimnion. Chemocline is separating layer that is based on chemistry gradients. It is present just below metalimnion. Epilimnion is the topmost layer of water that is directly exposed to air and solar irradiation, making it warmer compare to other layers.

B. Power of Hydrogen

The power of hydrogen (pH) is defined by the number of hydrogen ions in solution. It is the negative base 10 logarithm of hydrogen ion in any solution. The logarithmic scale denotes that when pH level increases, the concentration of hydrogen ion decreases by power of 10. The exothermic reaction denoted in (6) shows that as water temperature increases, there is corresponding decrease in ions present in water resulting to decreasing pH. Water temperature has high opportunity to vary the pH of water without adjusting its acidity and alkalinity.

$$pH = -\log_{10}[H^+] \tag{5}$$

$$H_2O \leftrightarrow H^+ + OH^- \tag{6}$$
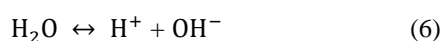
Continuous pH monitoring is necessary because it has substantial impacts to aquatic organisms and ecosystem. If it is too high or too low, aquatic organisms especially fishes die. Generally, pH level of 7.0 to 9.0 is the most suitable range for fish cultivation and plant growth. The varying pH level even affects the solubility of chemicals and the toxicity of heavy metals present in water. Slight intensification in pH level results to changing an oligotrophic boy of water to eutrophic. This pertains to the reduction of dissolved oxygen that is predominantly present in an aquatic system. A chain reaction happens when pH level varies, yielding unbalanced nutrients in the aquatic system. In fact, pH has direct root from carbon dioxide (CO_2) fluctuations. The biological processes in aquatic resources such as photosynthesis, biotic respiration and decomposition are the major contributors of CO_2 buffering that alters pH concentration.

III. SYSTEM ARCHITECTURE FOR OPTIMIZATION

There are numerous optimization techniques such as ant colony and bacteria foraging but genetic algorithm (GA), water cycle algorithm (WCA), enhanced vibrating particles system (EVPS), simulated annealing (SA) and particle swarm optimization (PSO) were chosen for its simplicity and capability in finding optimal solution to specific problem [15]. These metaheuristic evolutionary techniques determine the best condition based on imperfect and partial information. The main characteristic of the proposed system is the use of the abovementioned metaheuristic algorithms in determining its suitability in optimizing environmental data-driven descriptors. Matlab is the development platform used in constructing the codes for each model.

Fitness function is otherwise known as evaluation function which determines the fitness of a solution to the desired problem. Mathematically, it is the function to be minimized. Normally, fitness function constructed in the form of Euclidean distance (ED) and Manhattan distance (MD) was used as a measure for classification error in supervised machine learning. It is the numerical expression representing the effectiveness or performance of individual chromosomes in a phenotype or particle in a system. In this study, a temperature-pH eigen-ammonia factor model was employed and is shown in (7). The A is the dependent eigen-ammonia factor, temp is the global temperature of the aquatic pond measured in °C and pH is the hydrogen ions concentration of the same aquatic pond. Using multiple linear regression (MLR), the mathematical model of (7) was constructed and is translated to its fitness function form as shown in (8). The x_1 resembles the water temperature and x_2 for the water pH level.

$$\begin{aligned} A = 0.00299 &+ 0.000141(temp) - 0.002239(pH) \\ &+ 0.000005(temp)^2 + 0.000454(pH)^2 \\ &- 0.000086\,(temp)(pH) \end{aligned} \tag{7}$$

$$\begin{aligned} f(x_1, x_2) = 0.00299 &+ 0.000141 * x_1 - 0.002239 * x_2 \\ &+ 0.000005 * x_1{}^2 + 0.000454x_2{}^2 \\ &- 000086 * x_1 * x_2 \end{aligned} \tag{8}$$

A. Genetic Algorithm

Genetic algorithm belongs to a larger class of evolutionary

algorithms (EA) which represents its optimization solution as strings of numbers that is technically called as chromosomes, then eliminates the worst solution and breeds new solution from the derived set of best solutions.

Any aquatic body requires stable combination of pH and temperature levels for certain duration as the aquatic species mature and the requirement of hydroponic plants to grow is based on. Unmonitored and uncontrolled impacts of pH and temperature in water significantly results to varying ammonia factor that provides detrimental algal bloom phenomena, fish death and toxification of cultivating plants. As temperature increases, pH decreases in general cases. But this is not always the case due to other environmental and biochemical factors affecting the balance of the system, though pH and temperature are the substantial impacting components for ammonia factor.

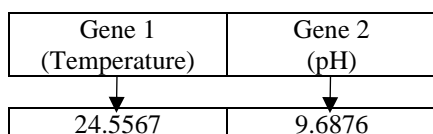| Gene 1 (Temperature)	Gene 2 (pH)
24.5567	9.6876

Fig. 1. Genotypic representation of chromosome data structure samples.

The data structure of chromosome in evolutionary algorithms is defined in a vector matrix form of N_{ind} x L_{ind} where N_{ind} and L_{ind} are the number of individuals in the population and the length of the genotypic representation of each individual, respectively. The genotypic component representation of a single set of gene for this study is represented in Fig. 1. There are two independent genes corresponding to the chromosome. The unit used for measuring temperature is °C.

The initial generation was set to 50 chromosomes because of the default standards to be applied for five or fewer genes. It means that there are 50 individuals present in each generation. The random generator was used to initialize the genes for the entire search space. It is characterized by uniform distance structure of genes with equal length bases of varying genotypes. The population type used was double vector and the initial range is from -10 to 10. This is the population type used because of the presence of integer constraint. The collected temperature and pH data using the developed aquatic mote were used as key parameters to the system. The only constraint used in this study is the set of bounds. The lower and upper bounds for the chromosomes are set to [0 6.5] and [35 10] respectively. The fitness scaling used is rank. It scales the raw scores based on the rank of each gene in which the fittest individual is rank 1, the next fittest individual is rank 2 and the like.

To breed a new generation of population, the fitness value is computed and the best chromosomes from the entire search space are selected. Selection is otherwise known as elitism for retaining the best individuals in a generation unchanged for the next generation. These selected best individuals become the parents for the next generation. The generic approach of selection implementation starts with the evaluation of each individual in the generation using the fitness function, then normalization of each fitness value. The fitness values are then sorted in descending manner. There are several selection techniques that evaluates the fitness of each gene and selects the best solution from the solution such as stochastic uniform, remainder, uniform, shift linear, roulette

and tournament [16], [17]. In this study, the tournament selection method was employed. It randomly selects each parent from the whole population with a tournament size of 4 due to the selection pressure provided to each individual. The chromosome with the best fitness among the population is considered as the winner. It is selected to be the parent chromosome for the next process that is crossover. The genetic algorithm optimizes the succeeding genes through a selection pressure that entails the likelihood of each chromosome to take part in the tournament given that each genotype is unique. The unfit chromosomes are rejected from the generation and the fittest chromosomes produce the next generation through reproduction. The reproduction process of genetic algorithm describes the creation of offspring for each new generation. The elite count used is 2.5 that is 5% of the total population size. It describes the number of assured individuals to continue to the succeeding generation. The crossover fraction rate is 0.8.
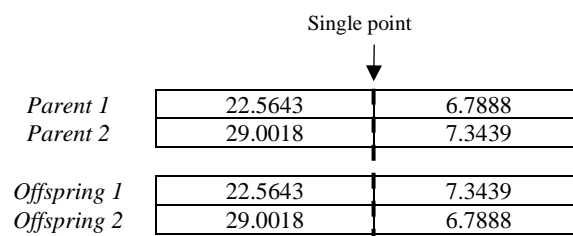
Single point

Parent 1	22.5643	6.7888
Parent 2	29.0018	7.3439
Offspring 1	22.5643	7.3439
Offspring 2	29.0018	6.7888

Fig. 2. Genotypic representation of single point crossover.

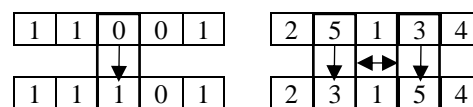| 1	1	0	0	1		2	5	1	3	4
1	1	1	0	1		2	3	1	5	4

Fig. 3. Sample 5-bit string mutation and integer mutation.

Crossover is otherwise known as genetic recombination given the fact that it merges the genetic information of two parents to produce offspring. The characteristics of the two parent chromosomes are extracted and yields a partial generated gene that will be supplemented to the existing generation after it undergoes mutation. The different crossover techniques are constraint dependent, scattered, single point, two point, intermediate, heuristic and arithmetic.

In this study, the single point crossover technique was employed which describes that a single characteristic from the parent may vary for each offspring. Fig. 2 shows the genotypic representation of single point crossover of two parents and two offspring chromosomes. It is noticeable that only one characteristic or parameter from the parent chromosome had crossover for each of the two offsprings.

Mutation introduces random genetic diversity to each chromosome in the population which already surpassed crossover. It reduces two or more chromosomes becoming identical. The different mutation techniques are constraint dependent, gaussian, uniform, and adaptive feasible. In this study, uniform mutation technique was employed with mutation rate of 0.01. The uniform mutation chooses a fraction of chromosomes from the population having identical probability of 0.01 of being mutated then it substitutes each selected individual with uniformly selected number from the population. Fig. 3 shows the mutation for bit string and integer string. Mutation changes one bit in the bit

stream at a location for each time. If the fitness value of the chromosome being mutated is better compared to the current fittest chromosome, it will not be considered as the new best chromosome.

B. Simulated Annealing

Simulated annealing is a metaheuristic that provides solution in searching for the global minimum instead of having premature localization of a minima throughout the iteration process based on a given function [18], [19]. The iteration process starts with an initial temperature that decreases for each iteration (i) with several steps based on the constraint of iteration time that was set in the model. The temperature starts as much as possible not close to zero and generates successors randomly. The energy function is then evaluated. If the function value is lower than the previous value, then the current function is valuated otherwise it will proceed to chose random probability. Then, the annealing function dictates to continue the search of the global minima and evaluates the function. The initial temperature decreases as it nears the stop iteration.

In this study, fast annealing and Boltzmann annealing were used as annealing functions in calibrating the optimization models. The hyperparameters are reannealing interval and initial temperature. The reannealing interval was set to 100, 300, 600 and 900, and the initial temperature was set to 100 to 1000 with an increment of 100. The maximum iteration was set to 1000. The modeling incurred by these hyperparameter variations resulted to specific minimum function (f_{min}) value, and optimized temperature and pH concentration descriptors.

C. Water Cycle Algorithm

The water cycle algorithm is a metaheuristic approach in solving case-specific localization that typifies the process of water flow from streams to rivers and from rivers to seas [20], [21]. In minimization problem such as what this study is concerned about, the initial population is brought by the raining process which randomly initiates the number of streams. The best individual represented by the stream is determined if that stream constitutes the minimum cost function value. The iteration process that mimics the water flow process starts by assuming that streams flows into a global sea and if a specific stream yields more optimal function value compared to the currently known sea, that stream will be considered as the new global minimum or sea.

In this study, the hyperparameters are population size (N_{pop}), number of rivers and sea (N_{sr}), and evaporation condition constant (d_{max}). The N_{pop} was varied from 50 to 100 in an incremental step of 50. The N_{sr} was set to 4, 10 and 17 and d_{max} was set to 1×10^{-5} to 1×10^{-90} with increments of 1×10^{-10}. The maximum iteration value was set to 1000. The lower and upper bounds for temperature and pH were set to [16 6.5] and [40 11] respectively. This modelling also records the elapsed time for processing the designed model as basis in choosing the least computational cost approach.

D. Enhanced Vibrating Particles System

The enhanced vibrating particles system employs the principle of a one degree of freedom (DOF) system with consideration of the effect of viscous damping [22], [23]. The optimization process starts with the evaluation of the objective function and considers the particle HB as the historically best position of all individuals. Until the set iteration is not met, the good particle (GP) and bad particle (BP) are randomly selected based on weights whether as partially best and partially worst evaluations. The harmony memory considering rate regenerates the worst particles as violated individuals. Then, the value of the objective function is evaluated and reconsiders a new HB particle pertaining to the optimization coordinates. For EVPS, it is a model that the memory size is first considered as the HB before the first evaluation of the objective function.

In this study, the hyperparameters are population size (N_{pop}), pitch adjusting rate (PAR), harmony memory considering rate (HMCR) and memory size. The N_{pop} was set to 50 by default, the PAR to 0.1, 0.5, 0.7 and 0.9, the HMCR to 0.4, 0.6, 0.8, 0.95 and 1, and the memory size to 4, 6, 8, 10. The default values for maximum iteration, weights w1 and w2, and alpha are 1000, 0.3, 0.3 and 0.05 respectively. The lower and upper bound was set globally to 0 and 40. The neighbor value which handles the side constraints was also varied from 0.2 to 1 with incremental step of 0.1.

E. Particle Swarm Optimization

The particle swarm optimization is a metaheuristic and stochastic approach of swarm intelligence that is a considered a form of evolutionary computation (EC) [24]. The iteration process starts with initialization of population through the number of particles varying in position and velocity. The fitness function is evaluation based on the previous and current particle states. For minimization function, if the fitness function value is greater than the fitness value of the currently considered best particle, the latter stays as the best particle, otherwise it will be replaced by a new local minimum exploited by the newly evaluated fitness function. Then, the velocity and position of the global best particle are updated. It will be repeated multiple times based on the number of iterations that has been set until such iteration that the system will yield the global minimum [25].

In this study, the hyperparameters are swarm size, inertia range, self-adjustment weight and the social adjustment weight. The swarm size was set to 20, 50 and 100, the inertia range to 0.4, 0.7 and 1, the self-adjustment and social adjustment weights to 1.5, 1.75, 2, 2.25 and 2.5. The lower and upper bounds were set to 0 and 100 for both temperature and pH concentrations. This shows one of the limitations of PSO. The maximum iteration was set to 1000.

IV. OPTIMIZATION USING METAHEURISTIC MODELS

The main objective of this study is to verify and evaluate the suitability of metaheuristic models in determining the optimum conditions for trophic state assessment in terms of ammonia factor that is hardly affected by water temperature and pH concentration. As seen from Fig. 4, ammonia factor increases not only in the upper values of independent parameters. Potential ammonia factor exists also even if water temperature is low. In Fig. 5 and Fig. 6, water temperature and pH concentration have varying effects on the ammonia factor emitted by the aquatic pond. As the water temperature increases, the ammonia factor considerably increases given that majority of the water temperature lies between 15 °C and

30 °C. In that range ammonia factor dominantly yields between 0 to $2x10^{-3}$ concentration. The pH level has the same impact with temperature to ammonia factor. Majority of pH concentration lies between 6 and 10 levels and constitutes an ammonia factor dominantly ranging less than $2x10^{-3}$ concentration. Fig. 4 depicts the yielding effects of varying the two optimization variables, water temperature and pH concentration, to water gaseous ammonia factor. It is evident that ammonia factor with highest accumulated concentration happens for eight distinct combined cases of water temperature and pH as follows: 19.3 °C and 8.1, 20.4 °C and 8.3, 22.7 °C and 8.7, 26 °C and 9, 26.7 °C and 9.1, 27 °C and 9.1, 25.8 °C and 9.1, and 23.4 °C and 8.8. On the other hand, ammonia factor troughs for seven distinct combined cases of water temperature and pH as follows: 16 °C and 6.6, 15.9 °C and 6.6, 19.1 °C and 7.8, 19.7°C and 8, 20.8 °C and 8.2, 25.3 °C and 8.7, and 27.1 °C and 8.9.
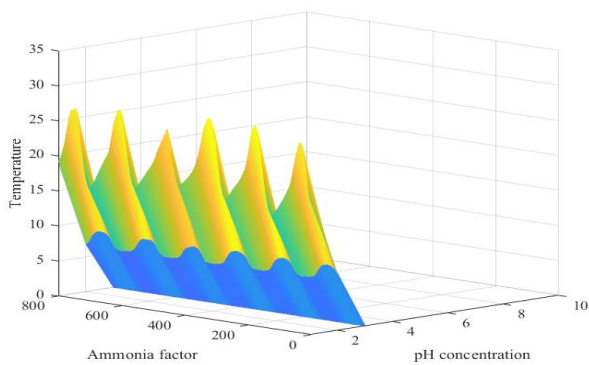

Fig. 4. Interaction of water temperature and pH concentration on ammonia factor.
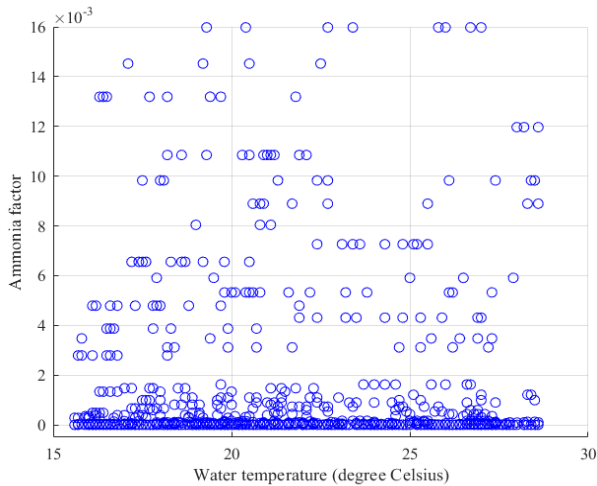

Fig. 5. Effect of water temperature on ammonia factor.

In optimizing the temperature-pH eigen-ammonia factor model of an aquatic pond as a eutrophication pollution emission parameter using genetic algorithm, the fixed values are the two optimization variables which are water temperature and pH level, the number of generations of 200 and the initial population size of 50 chromosomes. The primary varying parameters are the genetic operators which are the selection rate, crossover rate and mutation rate.

Fig. 7 to Fig. 9 depicts the fitness responses of each population size for varying selection rate, crossover rate and mutation rate. The lowest fitness value is considered the best for each modeling technique because GA is implemented in

this study for minimization of the fitness function. In Fig. 7, the selection rate that yielded the best three fitness response has value of 0.2, 0.1 and 0.4 respectively, with population size of 50 having the best fitness response. In Fig. 8, the crossover rate that yielded the best three fitness response has value of 0.8, 0.9 and 1.0 respectively, with population size of 50 having the best fitness response. In Fig. 9, the mutation rate that yielded the best three fitness response has value of 0.01, 0.03 and 0.04 respectively, with population size of 50 having the best fitness response. After several explorations, the GA model that provides the optimal values for water temperature and pH concentration for minimized ammonia factor is shown in Table 1 with its genetic operators.

The developed GA model was critically designed to produce the optimized values of independent parameters based on the fitness function of Eq. 8. It only means that outside of the GA-produced optimum values, ammonia factor may strengthen and result to eutrophication.
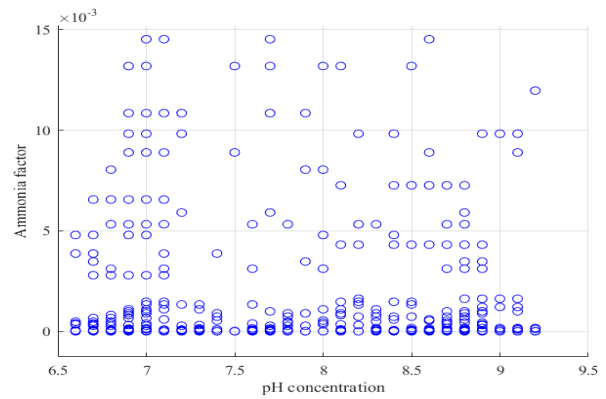

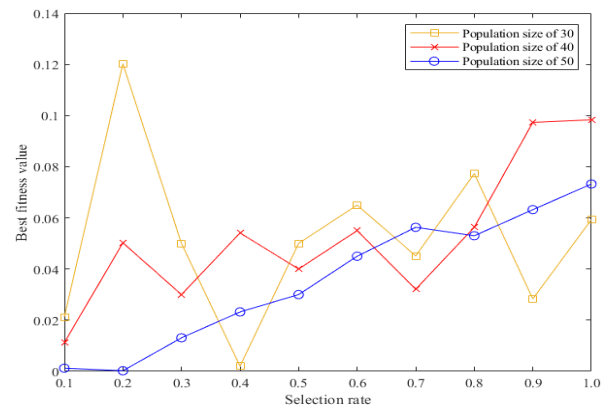Fig. 6. Effect of water pH concentration on ammonia factor.

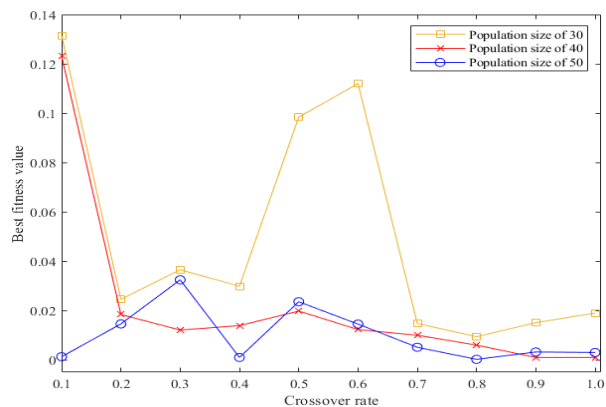Fig. 7. Fitness response with varying selection rate.
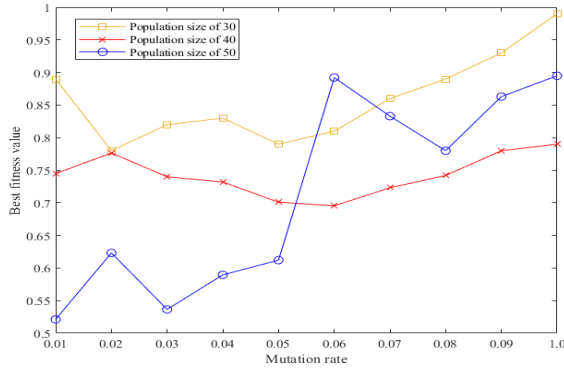

Fig. 8. Fitness response with varying crossover rate.

Fig. 9. Fitness response with varying mutation rate.

TABLE I: SUMMARY OF EMPLOYED GENETIC OPERATORS

Genetic operator	Value
Population size	50
Tournament size	4
Reproduction elite count	2.5
Selection rate	0.2
Crossover rate	0.8
Mutation rate	0.01
Migration fraction	0.2

The best fitness plot of the generated GA model describes the average costs per population and the best individuals and is shown in Fig. 14a. The value of the fittest individual is 0.000233879 and the average population fitness is 0.000234466.

In optimizing the temperature-pH eigen-ammonia factor model of an aquatic pond as a eutrophication pollution emission parameter using simulated annealing, the primary varying parameters are the function type of fast annealing and Boltzmann annealing. Shown in Fig. 10 is the difference of the elapsed processing time given the same reannealing interval with varying initial temperature to verify the complex capability of the two tested annealing functions. the elapsed time for fast and Boltzmann annealing are 59.1842 s and 28.0863 s respectively. Both functions yielded almost a constant function value of -0.0011. Table II shows the summary of employed simulated annealing hyperparameters that yielded the optimum ammonia factor to mitigate increase of eutrophication level. The best fitness plot of the developed SA model is shown in Fig. 14b. The value of the fittest individual is -0.0014 and the average population fitness is -0.0011.
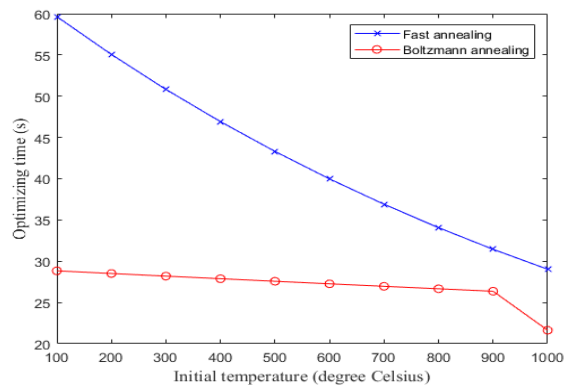

Fig. 10. Time response with varying initial temperature and annealing function.

TABLE II: SUMMARY OF EMPLOYED SA HYPERPARAMETERS

Simulated annealing operator	Value
Annealing function	annealingboltz
Reannealing interval	900
Initial temperature	1000

In optimizing the temperature-pH eigen-ammonia factor model of an aquatic pond as a eutrophication pollution emission parameter using water cycle algorithm, the primary varying parameters are population size, number of rivers and sea and the evaporation condition constant. The variation of evaporation condition constant against the optimizing time was is shown in Fig. 11 which has positive linear relationship. Table III shows the summary of employed water cycle algorithm hyperparameters that yielded the optimum ammonia factor to mitigate increase of eutrophication level. The best fitness plot of the developed WCA model is shown in Fig. 14c. The value of the fittest individual is -0.001133 and the average population fitness is -0.001132.
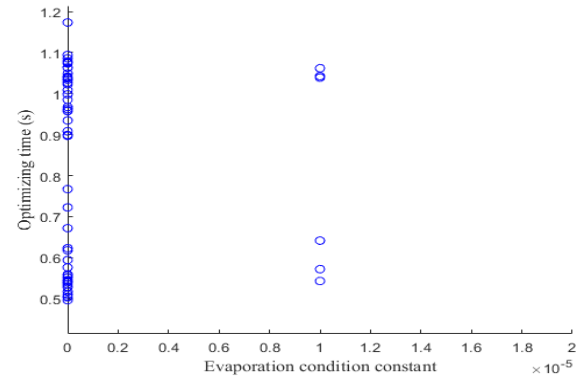

Fig. 11. Time response with varying evaporation condition constant.

TABLE III: SUMMARY OF EMPLOYED WCA HYPERPARAMETERS

Water cycle algorithm operator	Value
Population size	50
Number of rivers and sea	4
Evaporation condition constant	$1x10^{-10}$

In optimizing the temperature-pH eigen-ammonia factor model of an aquatic pond as a eutrophication pollution emission parameter using enhanced vibrating particles system, the primary varying parameters are the population size, pitch adjusting rate, harmony memory considering rate and memory size. Shown in Fig. 12 is the difference of pH incurred by varying the value of HMCR. It was noticed there is significant effect of changing the values of harmony memory considering rate to the value of optimized pH concentration. Table IV shows the summary of employed enhanced vibrating particles system hyperparameters that yielded the optimum ammonia factor to mitigate increase of eutrophication level. The average pH concentration for HMCR values of 0.4, 0.6, 0.8, 0.95 and 1 is 5.780833, 5.780839, 5.78167, 5.772038 and 5.783534 respectively. The best fitness plot of the developed EVPS model is shown in Fig. 14d. The value of the fittest individual is -0.0016 and the average population fitness is -0.0011.
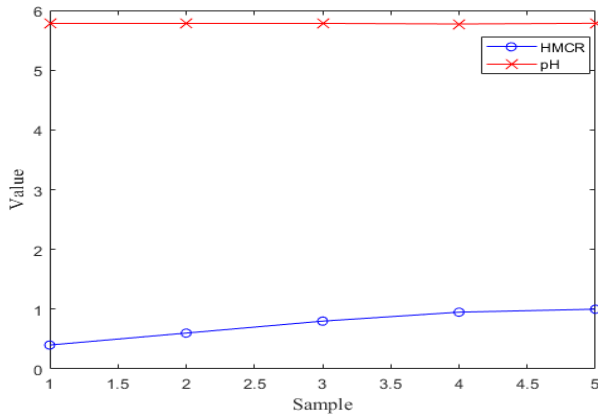
Fig. 12. pH concentration response with varying harmony memory considering rate.

TABLE IV: SUMMARY OF EMPLOYED EVPS HYPERPARAMETERS

EVPS algorithm operator	Value
Population size	50
Pitch adjusting rate	0.1
Harmony memory considering rate	0.8
Memory size	4

In optimizing the temperature-pH eigen-ammonia factor model of an aquatic pond as a eutrophication pollution emission parameter using particle swarm intelligence, the primary varying swarm size, inertia range, self-adjustment weight and social adjustment weight. Shown in Fig. 13 is the difference of the elapsed processing time given with varying self-adjustment weights. It was noticed there is significant effect of changing the values of self-adjustment weight to temperature level, pH concentration and elapsed optimizing time. The average temperature level for self-adjustment weight values 1.5, 1.75 and 2 is 38.47981 °C, 38.47435 °C and 38.47932 °C respectively. The average pH concentration for self-adjustment weight values 1.5, 1.75 and 2 is 6.120608, 6.119753 and 6.120915 respectively. The average pH concentration for self-adjustment weight values 1.5, 1.75 and 2 is 3.036674 s, 3.050728 s and 3.051258 s respectively. The best fitness plot of the developed EVPS model is shown in Table V shows the summary of employed particle swarm intelligence hyperparameters that yielded the optimum ammonia factor to mitigate increase of eutrophication level. Fig. 14e. The value of the fittest individual is -0.0015 and the average population fitness is -0.0011.
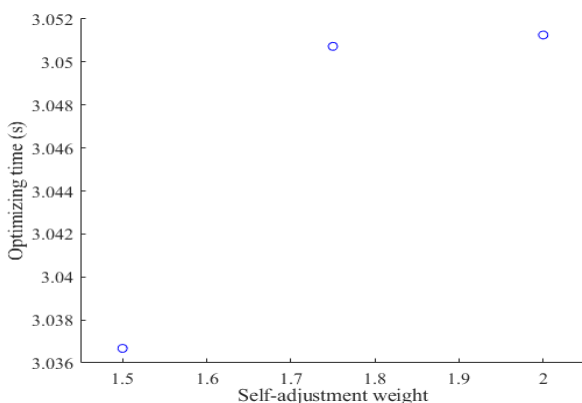

Fig. 13. Optimization processing time with varying self-adjustment weight.

TABLE V: SUMMARY OF EMPLOYED PSO HYPERPARAMETERS

EVPS algorithm operator	Value
Swarm size	20
Inertia range	[0.4 0.7]
Self-adjustment weight	1.5
Social adjustment weight	2.5

TABLE VI: COMPARATIVE RESULTS OF DEVELOPED METAHEURISTIC MODELS FOR OPTIMIZING AMMONIA FACTOR

Developed model	Optimum value	
	Water temperature	pH concentration
GA	29.254 °C	7.614
SA-FA	38.317 °C	6.095
WCA	33.317 °C	6.095
EVPS	35.000 °C	5.782
PSO	38.145 °C	6.079

Table VI shows the optimum values of ammonia-affecting parameters gained using the five developed metaheuristic models. As observed, WCA optimized with very fast processing time and SA is the direct opposite, specially when using fast annealing. GA, EVPS and PSO were used but numerous hyperparameters are needed to be adjusted to yield paramount results. On the other hand, EVPS searches more of the global minima using the maximum values of its hyperparameters, specifically, the pitch adjusting rate. PSO also positively adjusted its optimizing capability when using higher number of swarm size, for this case it is 50 and above. Using less than 50 swarm size resulted to erratic processing time.

GA yielded the best optimum values for temperature and pH concentration. The combination of 29.254 °C and 7.614 pH concentration results to minimized gaseous ammonia factor that renders oligotrophication in the aquatic pond. In this case, there is surmounting amount of dissolved oxygen necessary for fish growth and minimal volume of algal mass which allows light to enter underwater level for good nitrification process. Outside these two optimized values, there is high possibility of mesotrophication, eutrophication and hypereutrophication to materialize. Based on the study done by Laura Hu, the optimum range for water temperature and pH in aquaponics to maintain proper level of ammonia is 25 °C to 30 °C and 7.3 to 8.0, respectively [24]. Nitrifying bacteria which plays an important role in converting ammonia into nitrate and nitrite will die below 0 °C and above 49 °C. The nitrosomonas which converts ammonia to nitrites and nitrobacter which converts ammonia to nitrates grow in the pH range of 7.8 to 8.9 and 7.3 to 7.5. Hence, the generated optimized values for independent features agree the theoretical information.
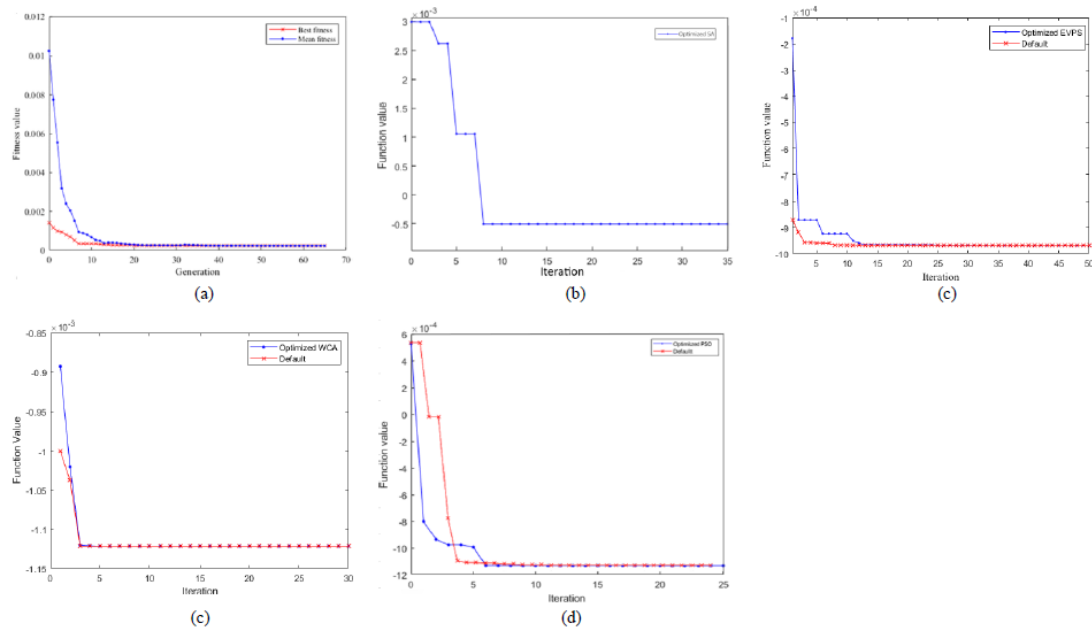
Fig. 14. Best fitness plot derived from (a) GA, (b) SA, (c) WCA, (d) EVPS and (d) PSO.

V. CONCLUSION

This study presented the suitability of metaheuristic algorithms application in soft computing the optimum values of water temperature and pH concentration to achieve minimized ammonia factor in avoiding eutrophication. Genetic algorithm, simulated annealing with fast annealing function, water cycle algorithm, enhance vibrating particles system and particle swarm optimization were critically modelled. Genetic algorithm yielded the best fitness plot with oligotrophication water temperature of 29.254 °C and pH concentration of 7.614. Having limnological parameters of these values renders no possibility for eutrophication to happen without the abrupt add-ons of anthropological actions on the balance of the system.

Future works include using other metaheuristic models and different approaches in constructing the hypothetical objective function to verify the effectiveness of optimization platforms for this kind of data.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

R. S. Concepcion II conceptualized the research, analyzed the data, developed the metaheuristic models and wrote the paper; A. A. Bandala, E. P. Dadios, and E. Sybingco helped in developing the models; S. C. Lauguico and J. D. Alejandrino performed the data collection and analysis.

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