A Fuzzy Genetic Method to Predict Air Demand Downstream of Bottom Outlet Gates

Mohammad Reza Kavianpour[i]; Mohammad Reza Najafi[ii]

ABSTRACT

With increasing the flow velocity over the surface of bottom outlet conduits and spillways of high dams, the potential for cavitation damage is also increased. Amongst various methods, aeration has been found as an effective and easy way to eliminate cavitation. Flow aeration improves the mean pressure and modifies the intensity of pressure fluctuations. So far, many works have been done and various relationships have been introduced to predict the quantity of entrained air downstream of outlet gates. However, there are uncertainties in using these expressions for various flow and geometry conditions. In recent years, the applications of artificial intelligence, such as neural networks, fuzzy logic, and genetic algorithm have attracted the attention of many investigators. They are known as powerful tools to solve engineering problems with uncertainties. Therefore, in this study, a model based on genetic algorithm was developed to express an equation for estimating the quantity of air demand downstream of gates in outlet conduits. Fuzzy logic was also adopted to control the system. The model is based on experimental information from various physical model studies. The measurements were made at Water Research Institute of Iran on several physical models of bottom outlet conduits, which are under construction or recently completed in Iran. The models mostly consists of service and emergency slide gates with fixed aerators on the top wall of the conduits. The proposed expression provides a good prediction of the quantity of required air as a function of the Reynolds and Froude numbers, the gate opening and the geometries of aerator, conduit and gate. Reasonable agreement between the predicted results and the experimental information proves the validity of the present model.

KEYWORDS

genetic algorithm, fuzzy genetic, aeration, bottom outlet conduit, fuzzy logic, cavitation, gate

1. INTRODUCTION

In recent years, the application of new computational methods has emerged as a powerful tool to model nonlinear systems, especially by introducing the theory of fuzzy sets. This technique is a powerful tool to deal with linguistic variables and variables of approximate nature [10]. The genetic algorithm (GA) is an optimization and search technique based on genetics and natural selection. This method was developed by John Holland (1975) and finally popularized by David Goldberg, who was able to solve a difficult problem involving the control of gas-pipeline transmission [2]. The work of De Jong (1975) showed the usefulness of the GA for function optimization and made the first concerted effort to find optimized GA parameters [3].

In this study, the combination of fuzzy system and genetic algorithm was developed to define an expression for flow aeration downstream of bottom outlet leaf gates. In the genetic algorithms, the operators such as crossover, mutation and their rates have strong influences in finding the best solution. In simple genetic algorithms, the mutation and crossover rates are established by the user and kept constant during the iterations. Thus, the operators depend on the knowledge and experience of the user [5]. In this study, the rates of crossover and mutation are dynamically controlled by fuzzy systems. After every iteration, the differences between two consequent results, whether it is negative or positive, are added to the fuzzy system.

To determine the quantity of air demand for various gate openings, the critical Froude and Reynolds numbers of flow, cross sectional area of the gates inside the conduit, and the cross sectional area of the aerators are used as inputs. The output of the model is

i M. R. Kavianpour, Assistant Prof., Civil Engineering Department, K.N. Toosi University of Technology, Tehran, Iran (e-mail: kavianpour@kntu.ac.ir)

ii M. R. Najafi, Senior Research Engineer, Water Research Institute, P.O.BOX: 16765-3461, Tehran, Iran (email: reza.najafi61@gmail.com)

$\beta = Q_a / Q_w$, where the quantity of air demand is Q_a and Q_w is the discharge of flowing water. In this study, the upstream and downstream cross sectional area of the conduit at the location of gates are identical. Thus, according to Figure 1(A), aeration occurs only from the upper edge of the jet.

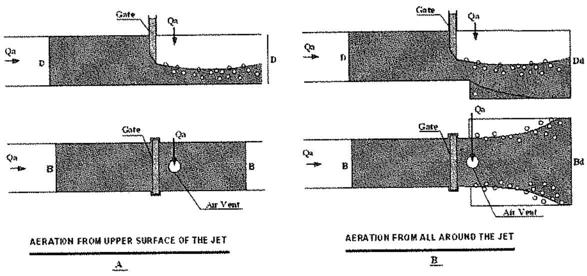

Figure 1: Schematic view of two mechanism of flow aeration.

2. GENETIC ALGORITHM (GA)

In classical methods, the optimum point of an equation, whether it is minimum or maximum is found by the derivation of the objective function. This is more likely to happen in which the algorithm finds a local maxima rather than the global maximum. However, by taking into account the evolution of the living organisms in this world, an algorithm has been suggested which is less likely to be trapped in local maxima and also does not need to derivate the objective function. A lot of advantages exist in this powerful algorithm, which can be found in many reference books.

The genetic algorithm starts by randomly generating some initial population which consists of so called chromosomes. Each chromosome includes unknown parameters that are to be found by the algorithm. This randomly selected initial population will evolve during each iteration of the algorithm called generation. Before any transfer of the chromosomes from one generation to another, some of the chromosomes will mate together to produce other chromosomes, having the characteristics of each parent chromosomes. In fact, genetic algorithms are grouped into two main ones, binary and real algorithms.

As mentioned, the offspring has the genes (unit data in a chromosome) of both of its parents, thus this operator makes the algorithm converge into a solution. Although by choosing a random population, the GA (genetic algorithm) is less likely to be trapped in local maxima or minima, still there is a potential for this problem. Therefore, another operator is being adopted in the algorithm which randomly changes some of the genes in some chromosomes. This operation distracts the algorithm from one special solution and makes it search other parts of the so called search space too. Determining the number of chromosomes to mate in a population and also the number of genes to be changed all depends on the crossover and mutation rates suggested by the user. After the mating and mutation, the population should go to the next generation. Actually in genetic algorithm, this process is called selection. Selection makes the groups of answers to evolve during each iteration, thus getting closer to the optimum point. Different methods have been suggested for this process, the simplest method is to choose some of the best chromosomes from the previous generation and make copies from the best one to the next stage.

3. STUDY OF FLOW AERATION

When the shear layer separates from the lip of the gate, abrupt changes in flow boundaries happen. It forms a recirculation zone, which is associated with mean pressure reduction and intense pressure fluctuations. As a result, the situation will be suitable for cavitation to occur [7]. In 1953, using venture-type cavitation apparatus, Peterka showed that for a 2% air concentration adjacent to the boundary, cavitation damage was greatly reduced and for a 6% to 8%, it was virtually eliminated [14]. Based on these results, various researchers tried to introduce relationships for predicting the quantity of air and to determine the size of aerators. The main studies are based on experimental results from specified physical models in the form of aeration coefficient (β), which is equal to the quantity of air (Q_a) to the quantity of water (Q_w).

In 1943, Kalinske and Robertson reported their results of air demand when a hydraulic jump forms inside conduit [6]. Based on their results, the aeration coefficient β was suggested as a function of Froude number (Fr), in the form of:

$$\beta = 0.0066(F_r - 1)^{1.4} \tag{1}$$

In 1953, Campbell and Guyton also suggested a similar equation [1]:

$$\beta = 0.04(F_r - 1)^{.85} \tag{2}$$

In 1964, for a free surface flow, in a partially full conduit with no hydraulic jump, the U.S. Army Corps of Engineers suggested the following relationship [18]:

$$\beta = 0.03(F_r - 1)^{1.06} \tag{3}$$

In 1965, Wisner also suggested the following relationship [19]:

$$\beta = 0.024(F_r - 1)^{1.4} \tag{4}$$

In 1976, Sharma classified the water flow in conduits and suggested the following equation for free flow conditions [16]:

$$\beta = 0.09Fr \tag{5}$$

In 2003, Kavianpour based on physical model studies, recommended the following two relationships as the upper and lower limits of aeration coefficients [7]:

$$\beta = 0.18(Fr - 1)^{.75} \qquad \text{Upper Limit} \tag{6}$$

$$\beta = 0.0012(Fr-1)^{1.39} \quad \text{Lower Limit} \qquad (7)$$

In 2005, Kavianpour made an investigation to check the validity of the expressions suggested for predicting air demand downstream of bottom outlet leaf gates [9]. The comparisons between these expressions and the physical model studies showed that a wide range of error from 110% to 550% is expected in using these expressions. His approach in 2005 to determine the air demand downstream of the gates using artificial intelligence techniques is unique and exceptional amongst previous investigations [8]. He applied neural networks to predict the air demand. The suggested artificial neural networks with a general back propagation error showed a very good estimation of air demand downstream of bottom outlet gates. The inputs to the ANN included the gate opening, aeration mechanism (aeration from one side or all around the jet), head of water upstream of the gate, the cross sectional area of the conduit at the gate location and the water discharge. The quantity of air was the output of the system.

Because of the wide range of errors arising in using those various expressions, the designers are usually obliged to establish new physical models to check the quantity of air demand and the size of aerator downstream of the gates in outlet conduits. Of course, it needs more money and time to finalize the design. Therefore, in this study, fuzzy genetic algorithm is used to introduce a better expression for estimating the quantity of air demand downstream of these gates.

4. GENETIC ALGORITHM ARCHITECTURE

Genetic Algorithm is based on finding the global maxima with a group of solution candidates. The process possesses a feature that species with the higher fitness function to environments are able to survive and evolve over many generations. Thus, those with the fitness function unable to survive, eventually become extinct due to the natural selection. The solution is based on that the natural selection is repeated to make species fitter to the evolution. Using the combination of solution candidates, genetic algorithm finds out the final one. The process is called the crossover operator.

In order to avoid the monotonous search, the drastic changes of the fitness function are created by the mutation of chromosomes with some probability and the combination of species with the lower fitness function. The process is effective to avoid getting stuck in local maxima. Depending on problems to be studied, a way of coding, crossover and mutation operations are necessary to select appropriate schemes. In particular, the probability of crossover and mutation operations is necessary to be investigated [11].

In the simple genetic algorithm, real variables are transformed in binary codes for problems with real numbers. This will improve the search. Populations are generated by random numbers and the natural selection is carried out to preserve better solution candidates. Then the crossover operation is used to create new individual and the mutation operation is used to change a part of individuals with low probability [17]. As genetic algorithms are distinguished from others by the emphasis on crossover and mutation, more recently much attention and effort has been devoted to improve them. More advanced genetic operators are based on fuzzy logic with the ability to adaptively or dynamically adjust the crossover and mutation during the evolution process. Figure 2 presents the block diagram of a fuzzy-controlled genetic algorithm, in which two online fuzzy logic controllers are used to adapt the crossover and mutation.

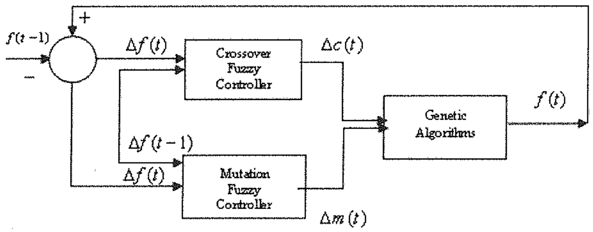

Figure 2: Block diagram of proposed fuzzy controlled genetic algorithm.

The fuzzy crossover controller is implemented to automatically adjust the crossover probability during the optimization process. The updating principles of the crossover probability is that, if the change in average fitness of the populations is greater than zero and keeps the same sign in consecutive generation, the crossover probability should be increased. Otherwise, the crossover probability should be decreased. The inputs to the crossover fuzzy logic controller are changes in fitness at two consecutive steps of $\Delta f(t-1)$ and $\Delta f(t)$, and the output of which is change in crossover $\Delta c(t)$. $\Delta f(t-1)$, $\Delta c(t)$ and $\Delta f(t)$ are normalized in the range of [-1,1], according to their corresponding maximum values. The crossover is computed by:

$$crossover(t) = crossover(t-1) + \Delta c(t) \qquad (8)$$

The mutation probability rate is automatically modified during the optimization process based on a fuzzy logic controller. The information for adjusting the mutation probability rate is that, if the change in average fitness is very small in consecutive generations, then the mutation probability rate should be increased until the average fitness begins to increase in consecutive generations. If the average fitness decreases, the mutation probability rate should be decreased. The inputs to the mutation fuzzy controller are the same as those of the crossover fuzzy controller, and the output of which is the change in mutation $\Delta m(t)$.

The design of the membership function, decision and action tables for the fuzzy mutation controller are similar to those for the fuzzy crossover controller. The membership functions used in the fuzzy controller are triangular. Figure 3 illustrates the membership functions. Table 1 is also the decision making table used in this model. Refer to the reference [17] for further information.

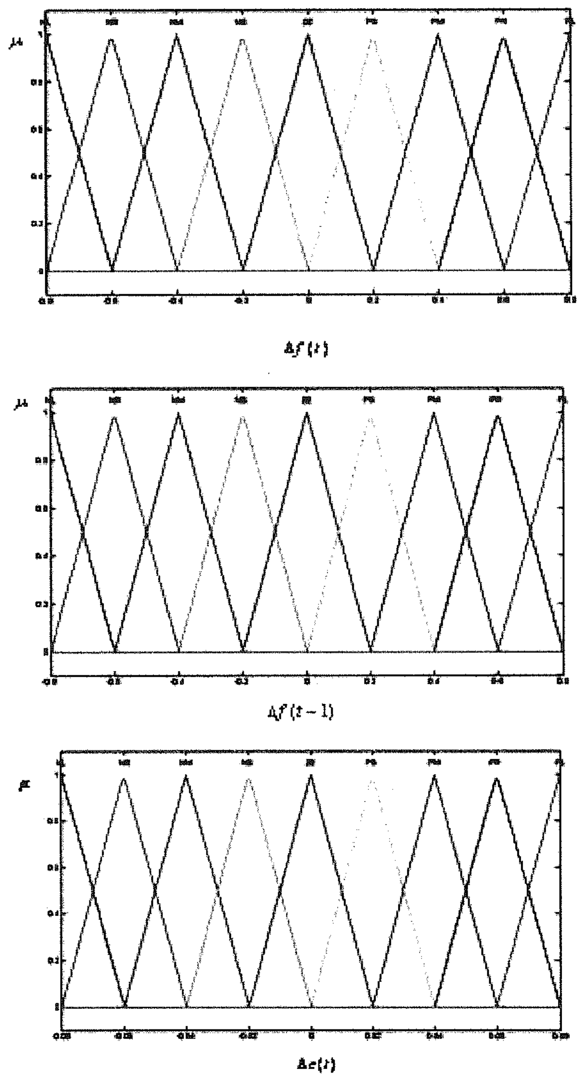

Figure 3: Triangular membership functions for inputs and outputs.

TABLE 1: DECISION MAKING TABLE.

$\Delta f(t)$ \ $\Delta f(t-1)$ ($\Delta c(t)$)	NL	NR	NM	NS	ZE	PS	PM	PR	PL
NL	NL	NR	NR	NM	NM	NS	NS	ZE	ZE
NR	NR	NR	NM	NM	NS	NS	ZE	ZE	PS
NM	NR	NM	NM	NS	NS	ZE	ZE	PS	PS
NS	NM	NM	NS	NS	ZE	ZE	PS	PS	PM
ZE	NM	NS	NS	ZE	ZE	PS	PS	PM	PM
PS	NS	NS	ZE	ZE	PS	PS	PM	PM	PR
PM	NS	ZE	ZE	PS	PS	PM	PM	PR	PR
PR	ZE	ZE	PS	PS	PM	PM	PR	PR	PL
PL	ZE	PS	PS	PM	PM	PR	PR	PL	PL

Note: (NL=negative larger, NR=negative large, NM=negative medium, NS=negative small, ZE=zero, PS=positive small, PM=positive medium, PR=positive large, PL=positive larger)

5. RESULTS AND DISCUSSION

In this study, a fuzzy genetic algorithm was developed in order to extract an expression for estimating the quantity of air demand downstream of gates in bottom outlet conduits. Around 60 data has been used for the purpose of this research from the physical models of Jareh, Alborz, Dasht-e-Abbas, Jegin, Karkheh, Kosar, Taham and Seymareh dams, which are under construction or recently completed in Iran.

The bottom outlet models of the mentioned dams have been made and tested at Water Research Institute of Iran. The scales of the models vary from 1:12 to 1:20. More information regarding the geometry and hydraulic characteristics of the models can be found in the work of Najafi [12]. For this set of data, air entrainment occurs only from the upper edge of the jet flowing beneath the gate (Figure 1).

Figure 4 shows a comparison of the results of previous expressions for air demand downstream of bottom outlet gates with the experimental information. The figure shows significant discrepancies between these expressions. For example, the value of aeration coefficient $\beta = Q_a/Q_w$ predicted by these expressions at Fr=21 varies from 0.1 to 2, which means that Q_a can be between $0.1Q_w$ to $2Q_w$.

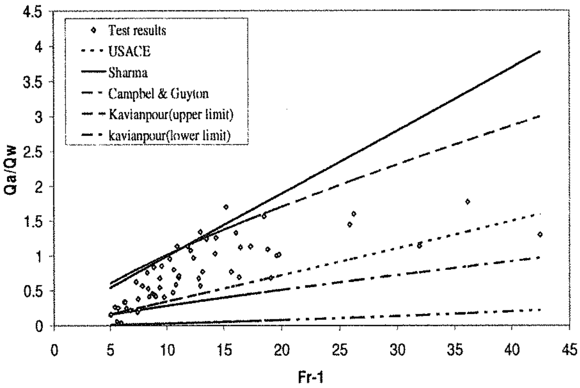

Figure 4: Comparison of the previous expressions for air demand with experimental results.

In this study, genetic algorithm controlled by fuzzy logic is developed to find the most important parameters and their arrangement in an expression for estimating the quantity of flow aeration downstream of outlet gates. The general form of this expression was suggested based on dimensional analysis as follow:

$$Q_{av} = f\begin{pmatrix} U_c, g, y_c, b_g, h_g, h_{g-w}, G, H_t, L_t, \\ A_a, A_d, \Delta p_a, \rho_a, \rho_w, \sigma_w, v_w \end{pmatrix} \tag{9}$$

In this equation, U_c and y_c are respectively the velocity and depth of flow at vena contracta and b_g is the width of the conduit. Also, ρ_w, σ_w, and υ_w are respectively the density, surface tension and viscosity of water and ρ_a is the air density. The height of the conduit downstream of the gate consists of the height of the gate which is usually filled with water and the height of cavity which is filled by air (h_{g-w}). Δp_a is the pressure difference downstream of the gate, g is the acceleration due to gravity, L_t is the downstream length of the tunnel and H_t is the head of water. The relative gate opening $G = h_w / h_g$ is determined based on the depth of water beneath the gate h_w and the height of the gate h_g. Also, A_a and A_g are the cross sectional areas of the aerator and the flow beneath the gate and A_d is the cross sectional area of the conduit downstream of the gate.

In this paper, based on previous investigations made by Rajabi [15], Nersesian [13], and Najafi [12] at K.N. Toosi University of Technology, the final proposed expression takes into account the Reynolds and Froude numbers, the gate opening and also the geometries of conduit and aerator in the following form;

$$\beta_c = a\,Frc^b \,\mathrm{Re}^c\, G^d (1-G)^e \left(\frac{A_a}{A_g}\right)^f \tag{10}$$

where a, b ,c ,d ,e and f are the unknown parameters to be optimized by fuzzy genetic algorithm. In this equation, $\mathrm{Re} = (U_c . y_c)/\upsilon$ and $Frc = U_c / \sqrt{g\, y_c}$ are respectively the Reynolds and Froude numbers of flow.

A function has been chosen which shows the difference between the results of model and experiments. The absolute sum of the errors was also obtained to make the fitness function. Now, in each iteration, the cost of all chromosomes is obtained through this function. The best chromosomes are the ones with the highest cost values, better to say, the fitness function value.

The process of the improvement of the chromosomes during iterations in the algorithm is shown in Figure 5. In this figure, the long generations are due to the developing procedure of the fuzzy genetic algorithm in comparison with the simple genetic algorithm. It is observed that the fuzzy genetic algorithm is improving much more in the generations, compared to simple genetic algorithm. The figure shows that even after 2500 iterations, as the mutation and crossover rates are dynamically changed, the fuzzy genetic algorithm is still improving.

To determine an expression for aeration ratio, considering *Frc* as the unique variable of β showed unsatisfactory results. But adding (1-*G*) to the expression to take into account the free space zone above the water jet, where *G* is the relative opening of the gate, provided more satisfactory results. Finally, the equation was improved by considering Re as the representative of turbulence intensity. Comparison of the results is shown in Figures 6 to 8. In these figures, βc and βe are respectively the calculated and experimental values of aeration ratio. Equations 11 to 14 also show the resultant expressions for β based on various variables used in this study. It is observed that regression (R^2) increases with considering more parameters in the expression of aeration coefficient.

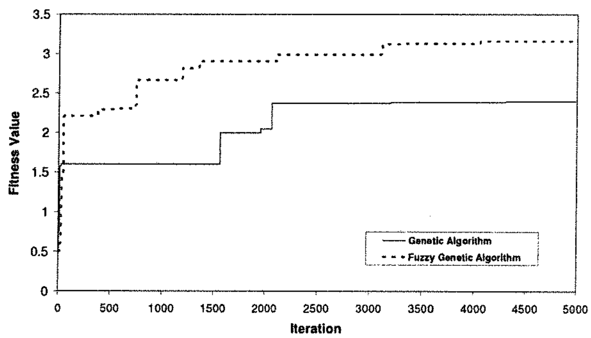

Figure 5: The improvement of the simple and fuzzy genetic algorithms during iterations.

$$\beta_c = 0.015707 Fr_c^{0.69279} \qquad R^2 = 0.580 \tag{11}$$

$$\beta_c = 2.9238 Fr_c^{1.2669} \left(\frac{A_a}{A_g}\right)^{1.6497} \qquad R^2 = 0.850 \tag{12}$$

$$\beta_c = 2.9476 Fr_c^{1.2222} (1-G)^{0.11655} \left(\frac{A_a}{A_g}\right)^{1.5932} \quad 0 < G < 1 \qquad R^2 = 0.857 \tag{13}$$

$$\beta_c = 1.1011 Fr_c^{2.8273} G^{1.9885} (1-G)^{1.313} \left(\frac{A_a}{A_g}\right)^{1.7715} \quad 0 < G < 1 \qquad R^2 = 0.959 \tag{14}$$

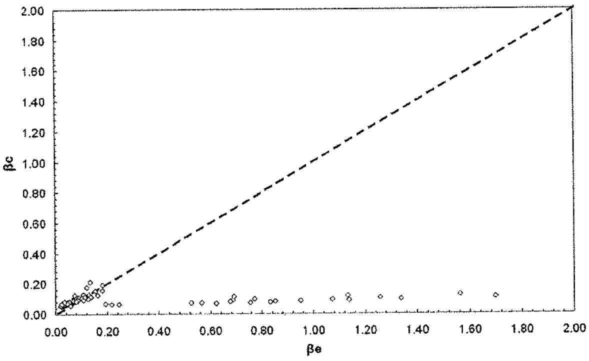

Figure 6: Variation of βe with βc for Equation (11).

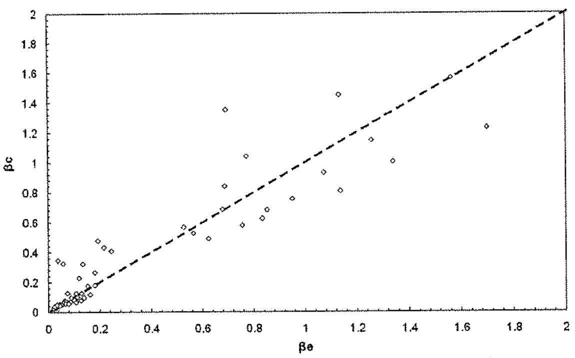

Figure 7: Variation of βe with βc for Equation (13).

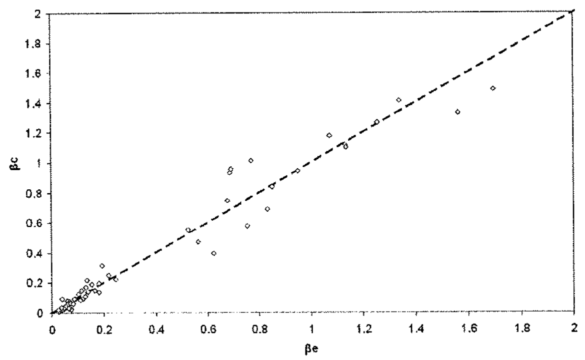

Figure 8: Variation of βe with βc for Equation (14).

After fuzzy genetic algorithm was improved, the unknown parameters of a, b, c, d, e and f were optimized by fuzzy genetic algorithm. The resultant expression based on these parameters is in the form of;

$$\beta_c = 0.8847 Fr_c^{3.728} Re^{-0.065} G^{2.579} (1-G)^{1.346} \left(\frac{A_a}{A_g}\right)^{2.022} \quad (15)$$

$$0 < G < 1$$

The results obtained by this expression were compared with those of experimental information in Figure 9. It is observed that the predicted values of aeration ratios by the present relationship are in reasonable agreement with those of experimental results. Analysis of the data showed a regression value of R2=0.964, which is very interesting.

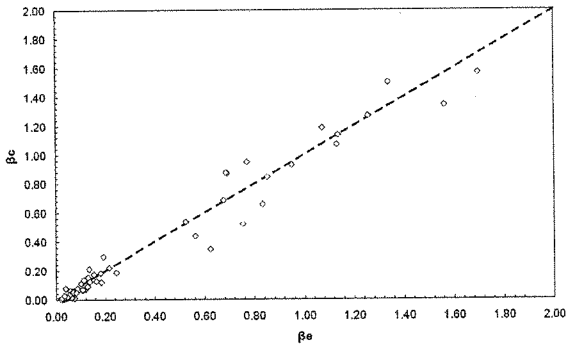

Figure 9: Variation of βe with βc for Equation (15).

6. Conclusion Remarks

In this study, a fuzzy genetic algorithm was implemented to extract an expression for predicting the quantity of air demand downstream of gates in bottom outlet conduits. Around 60 data from several physical models of bottom outlet dams have been used for the purpose of this research. Air entrainment was assumed to occur from only the upper surface of the confined jets. The final expression was obtained as a function of Reynolds and Froude numbers of flow, the gate opening and the geometries of the aerator and conduit in the form of equation 15.

Apart from Re which caused little improvement to regression value, the rest of parameters provided significant development to the final equation. These parameters were arranged with a regression value of R2=0.963. It should be mentioned that the results of previous expressions for determining of aeration ratio showed a wide range of error.

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