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نمذجة فعالية إنتقال الأكسجين في القنوات المبوبة بإستخدام برمجة التعبيرات الجينية

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الخلاصة

يتناول هذا البحث عملية إنتقال الأكسجين من الحالة الغازية إلي الحالة السائلة. تعتمد فعالية الإنتقال كلياً تقريباً علي مساحة السطح المتوفرة بين الهواء والماء. يمكن زيادة هذه المساحة بواسطة القنوات المبوبة التي تحتوي تدفق ثنائي من الهواء والماء. في السنوات الأخيرة تم إستخدام برامج الكمبيوتر لحل ظواهر كثيرة معقدة. إن برامج التعبيرات الجينية (GEP) مثال علي هذه البرامج . تم في هذه الدراسة إستخدام (GEP) للتنبؤ بفعالية إنتقال الأكسجين في حالة قنوات الضغط العالي والمساحة المفتوحة. إن مقارنة النتائج المختبرية مع النتائج النظرية أظهرت معامل إرتباط (R2) عالي جداً ومربع متوسط الخطأ (MSE) منخفض جداً. لذا فإن نماذج (GEP) تعتبر طريقة واعدة للتنبؤ بفعالية إنتقال الأكسجين في القنوات المبوبة.

The modeling of oxygen transfer efficiency in gated conduits by using genetic expression programming

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ABSTRACT

Oxygen transfer is the process by which oxygen is transferred from the gaseous to the liquid phase. The oxygen transfer efficiency depends almost entirely on the amount of surface contact between the air and water. This surface contact can be increased by gated conduits that involve air–water mixture flow. In reality, the physical structure of the air–water interface is complex and still awaits clarification. In recent years, different soft computing systems have been successfully employed for the solution of complex problems. Genetic expression programming (GEP) is an example of soft computing systems. This study presents the use of GEP based on a genetic algorithm to predict oxygen transfer efficiency in high−head and free−surface gated conduits. The comparison of experimental results with the results of GEP models revealed that correlation coefficients (R2) are very high and mean square errors (MSE) are very small. Therefore, GEP models are a fairly promising approach for the prediction of oxygen transfer efficiency in gated conduits.

Keywords: GEP; aeration; air–water flow; conduit; oxygen transfer.

INTRODUCTION

Currently there is much emphasis on water quality and maintaining water quality parameters in our freshwater hydrosphere. One of the most widely cited parameters is that of dissolved oxygen (DO) concentration. DO is often used as an indicator of the quality of water used by humans or serving as a habitat for aquatic flora and fauna. DO can range from zero to about 15 mg/L at saturation, depending on temperature and other characteristics of the water (such as salinity, pressure etc.). A higher DO level indicates better water quality. Aeration is the process of bringing oxygen into close contact with water in order to increase DO levels. Because of the large interfacial area generated by entrained bubbles, air–water flows in hydraulic structures have great potential to increase DO levels.

Recently, soft computing systems, such as neural networks, adaptive network based fuzzy inference system and least squares support vector machines, have been used in various areas of aeration-related research (Baylar *et al.*, 2007, 2008, 2009, 2011; Baylar & Batan 2010; Hanbay *et al.*, 2009a, b). Among soft computing systems, genetic expression programming (GEP) was developed by (Ferreira, 2001) using fundamental principles of the genetic algorithms (GA) and genetic programming (GP). The GEP process, which is like a biological process, is a computer program encoded in linear chromosomes of fixed-length. In GEP, a mathematical function is defined as a chromosome with multi genes and developed using the data presented to it.

The purpose of present study is to develop a model to predict oxygen transfer efficiency in high-head and free-surface gated conduits using GEP. GEP is preferred since it generates a mathematical function which fits given experimental data. Whereas, it is not possible to obtain a mathematical function with other soft computing systems. The developed models are based on experimental results of (Unsal 2007). Froude number at gate location and the ratio of the gate opening to the length of conduit downstream of gate are used as inputs and the output of the model is the oxygen transfer efficiency.

The paper consists of six sections. In section 1, an introduction of this study is presented. In section 2, the oxygen transfer process is summarized. In section 3, information about experimental processes are given. In section 4, the theory of genetic expression programming is outlined. In section 5, models developed by genetic expression programming are described. In section 6, conclusions are drawn.

Oxygen transfer process

The rate of oxygen mass transfer, i.e. from the gas (in this case air bubbles) to the liquid phase (water) is governed by the terms described below.

$$\frac{dC}{dt} = K_L \frac{A}{V} (C_s - C) \tag{1}$$

where C = Dissolved oxygen (DO) concentration; K_L = liquid film coefficient; A = surface area associated with the volume V, over which transfer occurs; C_s = oxygen saturation concentration; and t = time. The term A/V is often called the specific surface area, a, or surface area per unit volume.

$$\frac{dC}{dt} = K_L a (C_s - C) \tag{2}$$

Eq. (2) does not consider sources and sinks of oxygen in the water body because their rates are relatively slow compared to the oxygen transfer that occurs at most hydraulic structures due to the increase in free-surface turbulence and the large quantity of air that is usually entrained into the flow. The predictive relations assume that the DO concentration at saturation (C_s) is constant and determined by water-atmosphere partitioning. If that assumption is made, C_s is constant with respect to time, and the oxygen transfer efficiency (aeration efficiency), E may be defined as (Gulliver *et al.*, 1990):

$$E = \frac{C_d - C_u}{C_s - C_u} = 1 - \frac{1}{r} \tag{3}$$

where u and d = subscripts indicating upstream and downstream locations, respectively; and r = oxygen deficit ratio $[(C_s - C_u)(C_s - C_d)]$. A transfer efficiency value of 1.0 means that the full transfer up to the saturation value has occurred at the structure. No transfer would correspond to **E** = 0.

Comparative evaluations of oxygen uptake at hydraulic structures require that aeration efficiency should be corrected to a reference temperature. To provide a uniform basis for comparison of measurement results, the aeration efficiency is often normalized to a 20°C standard. Gulliver *et al.* (1990) proposed the following equation to describe the influence of temperature

$$1 - E_{20} = (1 - E)^{1/f} \tag{4}$$

where E = transfer efficiency at actual water temperature; E_{20} = transfer efficiency for 20°C; and f = exponent described by

$$f = 1.0 + 2.1x10^{-2}(T-20) + 8.26x10^{-5}(T-20)^2 \tag{5}$$

where T = water temperature. In this study, the oxygen transfer efficiency was normalized to 20°C using Eq. (4).

Mechanisms of air entrainment

If the gate of a high-head gated conduit is partly opened, a high velocity flow occurs downstream of it resulting in subatmospheric pressures (Fig. 1a). Theoretically, the pressure can be as low as the vapor pressure of water and may lead to structural damage due to cavitation. To avoid severe subatmospheric pressures the conduit is connected to the atmosphere through an air vent located downstream of the gate. Its purpose is to supply air and thereby keep the pressures downstream of the gate at a safe level (Sharma 1976).

The air suction mechanism of free-surface gated conduit is similar to that of high-head gated conduit. Free-surface gated conduit flow can be thought of as open-channel flow in a closed conduit (Fig. 1b). So far, much work has been done and various relationships have been introduced to predict air entrainment and oxygen transfer efficiency in high-head and free-surface gated conduits (Unsal 2007; Sharma

1976; Speerli 1999; Stahl & Hager 1999; Ozkan 2005; Ozkan *et al.*, 2006; Unsal *et al.*, 2008, 2009; Baylar *et al.*, 2010).

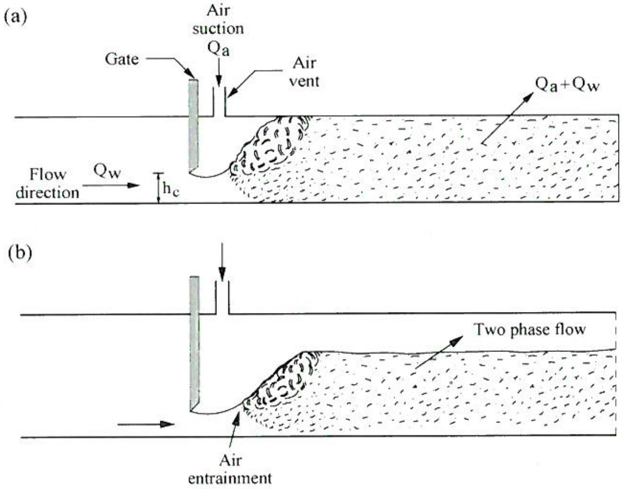

Fig. 1. (a) High–head gated conduit flow (b) Free-surface gated conduit flow

Experimental information

Unsal (2007) investigated the oxygen transfer efficiency in high-head and free-surface gated conduits. The results indicated that gated conduit flow systems were very effective for oxygen transfer. At high Froude numbers, almost full oxygen transfer up to the saturation value was achieved. The primary reason for this high oxygen transfer efficiency is that air is entrained into the flow in the form of a large number of fine bubbles. These air bubbles greatly increased the surface area available for mass transfer and hence the oxygen transfer efficiency.

Schematic representations of high-head and free-surface gated conduits used by Unsal (2007) are given in Fig. 2 (a-b). The air vent located downstream of the gate was 16 mm diameter. The gate opening h was varied from 1.6 cm to 4.8 cm in 1.6 cm increments and the conduit length L was varied from 2 m to 6 m in 2 m increments. During the experiments, DO and temperature measurements were taken upstream and downstream of the gated conduits. The oxygen transfer efficiency E_{20} was calculated from the measured values using Eqs. (3) and (4).

Tables 1 and 2 show the experimental results of Unsal (2007) that are used as the data in the present research. In these tables, Fr is Froude number at gate location defined by Eq. (6), h is gate opening, L is length of conduit downstream of gate, and E_{20} is oxygen transfer efficiency at the 20 °C.

$$Fr = \frac{V}{\sqrt{g\,h}} \tag{6}$$

where V is mean water velocity at gate location and g is acceleration due to gravity.

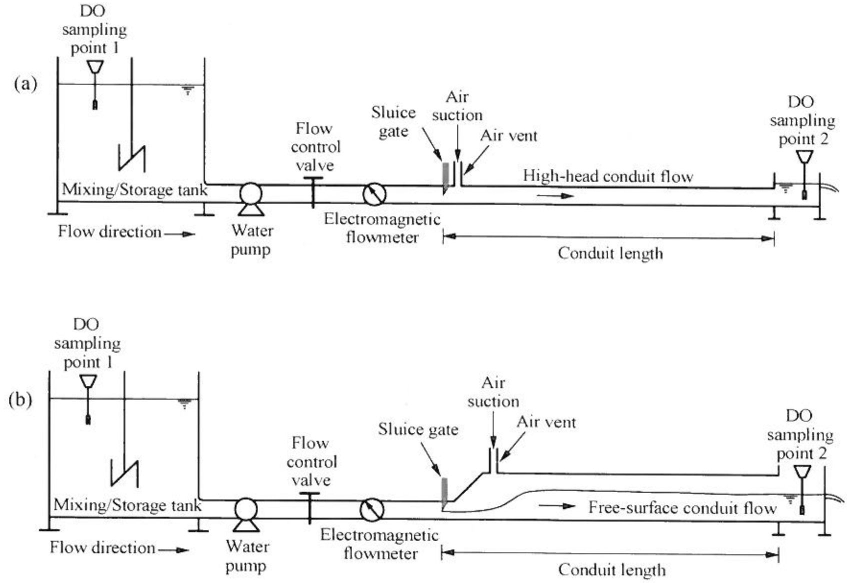

Fig. 2. Schematic view of flow aeration in
(a) high–head gated conduit and (b) free-surface gated conduit (Unsal 2007)

Table 1. Experimental data for high–head gated conduit (Unsal 2007)

No	Fr	h/L (10^{-3})	E_{20}	No	Fr	h/L (10^{-3})	E_{20}	No	Fr	h/L (10^{-3})	E_{20}
1.	5.479	8.00	0.210	*19.*	5.479	4.00	0.155	*37.*	5.479	2.67	0.224
2.	10.962	8.00	0.679	*20.*	10.962	4.00	0.488	*38.*	10.962	2.67	0.592
3.	16.439	8.00	0.838	*21.*	16.439	4.00	0.798	*39.*	16.439	2.67	0.814
4.	21.919	8.00	0.928	*22.*	21.919	4.00	0.917	*40.*	21.919	2.67	0.989
5.	27.399	8.00	0.964	*23.*	27.399	4.00	0.959	*41.*	27.399	2.67	1.000
6.	33.798	8.00	0.978	*24.*	32.223	4.00	0.972	*42.*	32.341	2.67	1.000
7.	3.574	16.00	0.162	*25.*	3.574	8.00	0.120	*43.*	3.574	5.33	0.207
8.	7.151	16.00	0.593	*26.*	7.151	8.00	0.496	*44.*	7.151	5.33	0.439
9.	10.728	16.00	0.788	*27.*	10.728	8.00	0.697	*45.*	10.728	5.33	0.794
10.	14.305	16.00	0.881	*28.*	14.305	8.00	0.842	*46.*	14.305	5.33	0.937
11.	17.882	16.00	0.934	*29.*	17.882	8.00	0.895	*47.*	17.882	5.33	0.900
12.	21.612	16.00	0.948	*30.*	21.795	8.00	0.932	*48.*	21.753	5.33	1.000
13.	2.726	24.00	0.096	*31.*	2.726	12.00	0.042	*49.*	2.726	8.00	0.192
14.	5.453	24.00	0.466	*32.*	5.453	12.00	0.269	*50.*	5.453	8.00	0.411
15.	8.178	24.00	0.662	*33.*	8.178	12.00	0.568	*51.*	8.178	8.00	0.650
16.	10.904	24.00	0.755	*34.*	10.904	12.00	0.689	*52.*	10.904	8.00	0.719
17.	13.630	24.00	0.802	*35.*	13.630	12.00	0.748	*53.*	13.630	8.00	0.778
18.	16.797	24.00	0.838	*36.*	16.622	12.00	0.799	*54.*	16.522	8.00	0.821

Table 2. Experimental data for free-surface gated conduit (Unsal 2007)

No	Fr	h/L (10^{-3})	E_{20}	No	Fr	h/L (10^{-3})	E_{20}	No	Fr	h/L (10^{-3})	E_{20}
1.	5.479	8.00	0.235	19.	5.479	4.00	0.014	37.	5.479	2.67	0.134
2.	10.962	8.00	0.666	20.	10.962	4.00	0.477	38.	10.962	2.67	0.424
3.	16.439	8.00	0.817	21.	16.439	4.00	0.753	39.	16.439	2.67	0.718
4.	21.919	8.00	0.900	22.	21.919	4.00	0.833	40.	21.919	2.67	0.846
5.	27.399	8.00	0.950	23.	27.399	4.00	0.889	41.	27.399	2.67	0.914
6.	32.419	8.00	0.969	24.	32.419	4.00	0.916	42.	32.419	2.67	0.936
7.	3.574	16.00	0.143	25.	3.574	8.00	0.027	43.	3.574	5.33	0.063
8.	7.151	16.00	0.584	26.	7.151	8.00	0.269	44.	7.151	5.33	0.355
9.	10.728	16.00	0.727	27.	10.728	8.00	0.607	45.	10.728	5.33	0.677
10.	14.305	16.00	0.862	28.	14.305	8.00	0.728	46.	14.305	5.33	0.831
11.	17.882	16.00	0.903	29.	17.882	8.00	0.781	47.	17.882	5.33	0.900
12.	21.278	16.00	0.945	30.	21.026	8.00	0.825	48.	21.278	5.33	0.934
13.	2.726	24.00	0.090	31.	2.726	12.00	0.060	49.	2.726	8.00	0.125
14.	5.453	24.00	0.464	32.	5.453	12.00	0.298	50.	5.453	8.00	0.348
15.	8.178	24.00	0.647	33.	8.178	12.00	0.539	51.	8.178	8.00	0.590
16.	10.904	24.00	0.750	34.	10.904	12.00	0.699	52.	10.904	8.00	0.792
17.	13.630	24.00	0.820	35.	13.630	12.00	0.825	53.	13.630	8.00	0.902
18.	16.311	24.00	0.877	36.	16.227	12.00	0.872	54.	16.409	8.00	0.931

Genetic expression programming (GEP)

Genetic expression programming (GEP) was developed by Ferreira (2001) using fundamental principles of the genetic algorithms (GA) and genetic programming (GP). GEP is a procedure that mimics biological evolution to create a computer program to model some phenomenon. The problems are encoded in linear chromosomes of fixed–length as a computer program. In other words, a mathematical function is described as a chromosome with multi genes and developed using the data presented to it. GEP performs the symbolic regression using the most of the genetic operators of genetic algorithm (GA). However, there are some differences between GEP and GA. Any mathematical expression defined as symbolic strings of fixed–length (chromosomes) in GA is represented to be nonlinear entities of different size and shapes (parse trees). But in GEP it is encoded as simple strings of fixed–length, which are subsequently expressed as expression trees of different size and shape (Munoz 2005; Cevik 2007).

GEP algorithm begins selecting the following five elements: function set, terminal set, fitness function, control parameters and stop condition. The basic GEP algorithm is shown in Fig. 3. This algorithm randomly makes up an initial chromosome, which represents a mathematical function and then converts it into an expression tree (ET), as shown in Fig. 4. There is comparison between predicted values and actual values in the subsequent step. When desired results in accordance with previously selected error criteria are found, the GEP process is terminated. If desired error criteria can not be found, some chromosomes are chosen by a method called roulette–wheel sampling and they are mutated to obtain new chromosomes. After a desired fitness score is found, this process terminates and then the knowledge is coded in genes within chromosomes that are decoded for the best solution of the problem (Teoderescu & Sherwood 2008).

GEP models are composed with two main components called chromosomes and the expression trees (ET). The chromosomes, which may have one or more genes, are coded with some information using special language about the problem. Any mathematical information is coded within genes in chromosomes using bilingual and conclusive language called Karva Language (the language of the genes) and also is translated to the expression trees by means of the language of ET. The Karva Language provides functional advantages in terms of precisely inferring the genotype.

Genes are divided into two parts; the head and the tail. The head of a gene includes chief variables used to code any mathematical expressions such as functions, variables, and constants. The tail includes exclusively variables and constants which may be required for additional terminal symbols, in case the variables in the head are incompetent to encode a function. The head of a gene includes arithmetic and trigonometric functions like +, –, *, /, $\sqrt{\ }$, sin, cos. The constants and the independent variables of the problem like 1, a, b, c are in the gene tail. The number of the symbols in the head and the tail defined the length of the head. It is a significant parameter in the GEP process and determined at the beginning of the analysis by the user. The ET is translated into Karva Language reading the ET from left to right in the top line of the tree and from top to bottom. The simple example of ET and its corresponding mathematical equation are illustrated in Fig 4.

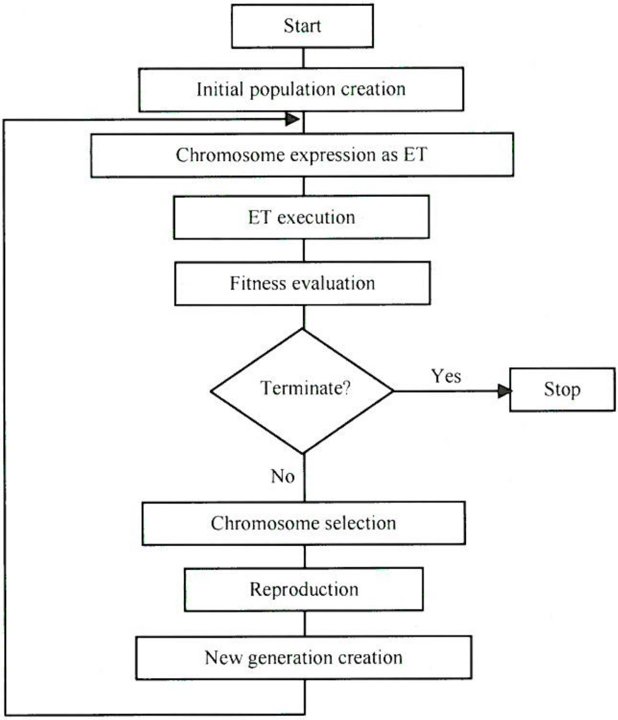

Fig. 3. The algorithm of genetic expression programming (Teoderescu & Sherwood 2008)

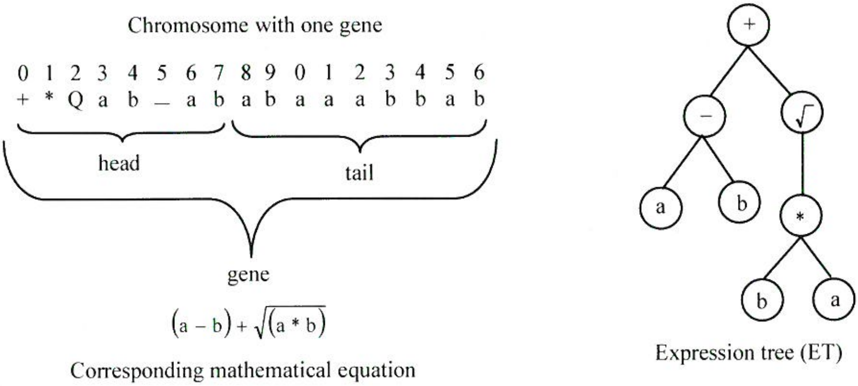

Fig. 4. Schematic indication of a chromosome with one gene and its expression tree and corresponding mathematical equation (Kayadelen *et al*., 2009)

GEP has some strength points. One strength of the GEP approach is that, the creation of genetic diversity is extremely simplified as genetic operators work at the chromosome level. Indeed, due to the structural organization of GEP chromosomes, any modification made in the genome results always in valid programs. Another strength of GEP consists of its unique, multigenic nature which allows the evolution of more complex programs composed of several sub-programs (Ferreira 2002).

The operators used in GEP

Every time the mathematical equation developed from a GEP model does not fit to problem. If so the chromosomes are mutated using GEP operators to obtain the next generation. GEP has four basic operators: selection, mutation, transposition, and cross–over (recombination). For the selection of any chromosomes, the selection operator uses a method called roulette–wheel sampling with elitism to obtain the higher probability of producing offspring. The mutation operator performs the mutation operation, changing the coding sequence in selected chromosome. However, during this process, the structure of the chromosome is not changed. On the other hand, a part of chromosome is fortuitously copied by transposition operator copies and put into another position. The coding of randomly selected two chromosomes is exchanged by means of cross–over (recombination).

The certain operator rates that define a certain probability of a chromosome are determined by the user before the analysis. It is proposed that the transposition rate and cross–over rate are 0.1 and 0.4, respectively (Sherrod 2008). The mutation rate is ordinarily employed between the 0.001 and 0.1 (Teoderescu & Sherwood 2008)

Result and discussion

In this study, two GEP models, GEP Model I (for high–head gated conduit) and GEP Model II (for free–surface gated conduit), are developed. Mathematical functions are generated by GEP models for the estimation of oxygen transfer efficiency in high–head and free–surface gated conduits. Thirty six of the 54 data sets given in Tables 1and 2 are used for training, and the remainder (18 of 54 data sets are used for testing of the models. In both models, two input parameters are utilized, such as Fr and h/L. Two mathematical functions are also generated in the form of $y = f\,(\mathrm{Fr}, \boldsymbol{h/L})$. Table 3 presents the model parameters used for both models. DTREG software is used for the GEP algorithm (Sherrod 2008). The mathematical functions generated for both conduits are given below:

Model I (High–head gated conduit) $\mathbf{R^2=0.948}$

$$E_{20}=\mathrm{Sin}[([\mathrm{Cos}(h/L)]/\sqrt{(\mathrm{Fr})})-\sqrt{\log(\mathrm{Fr})}]+\mathrm{Sin}([(\mathrm{Cos}(h/L))/(\mathrm{Fr}*(h/L))]-\sqrt{\log(\mathrm{Fr})})+(h/L)+\sqrt{\mathrm{Cos}[\mathrm{Cos}(\mathrm{Cos}[\log(\mathrm{Fr})])]} \tag{7}$$

Model II (Free–surface gated conduit) $\mathbf{R^2=0.941}$

$$E_{20}=\mathrm{Arctan}(\mathrm{Arctan}[\mathrm{Cos}(\sqrt{\log[\mathrm{Fr}+(h/L)]^3})])+\mathrm{Arctan}[\mathrm{Cos}(\sqrt{\log[(\mathrm{Fr}*\mathrm{Fr})*(\mathrm{Fr}*(h/L))]})]+\mathrm{Cos}[\mathrm{Arctan}([\sqrt{\sqrt{(\mathrm{Fr})}}]+\mathrm{Sin}[\mathrm{Fr}+(h/L)])] \tag{8}$$

Table 3. Parameters for GEP models

Parameters	Model I	Model II
Population size	30	30
Generation	87104	35119
Number of the genes	3	3
Length of the gene head	7	7
Linking function	+	+
Function set	+, –, *, /, $\sqrt{}$, sin, cos	+, *, /, $\sqrt{}$, sin, cos, arctan
Mutation rate	0.044	0.044
One–point recombination rate	0.3	0.3
Two–point recombination rate	0.3	0.3
Inversion rate	0.1	0.1
Transposition rate	0.1	0.1

The performances of the models are investigated by means of some statistical evolution criteria, such as correlation coefficient (R^2) and min. square error (MSE). The test results from GEP Model I and GEP Model II are compared with experimental results in Figs. 5 and 6. It is observed from these figures that high correlations are obtained. R^2 values of GEP Model I and GEP Model II are 0.948 and 0.941, respectively. It is accepted that R^2 value of any model is not sufficient for the statistical performance. Therefore, the error distribution of the models must be examined. In this study, min. square error (MSE) is adopted as statistical error criteria. MSE of the GEP Model I and GEP Model II are 0.0076 and 0.0075, respectively.

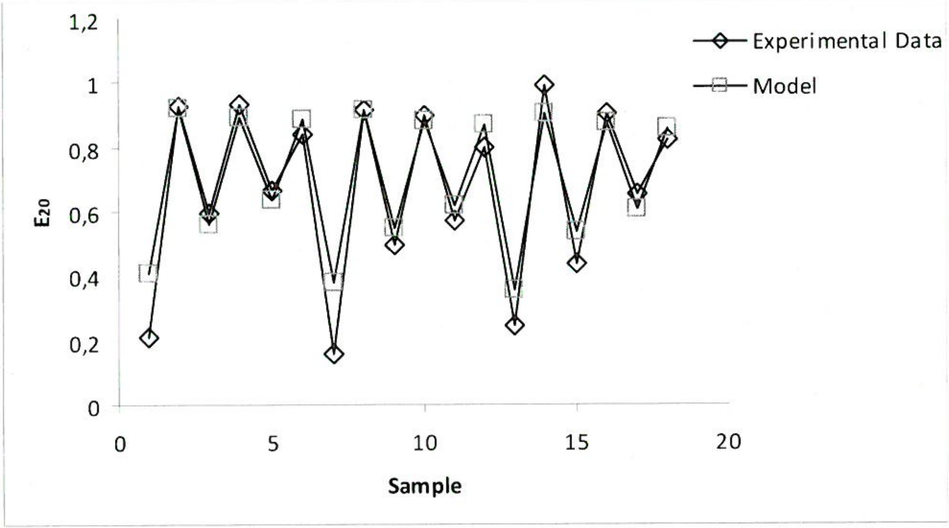

Fig. 5. The predicted and measured E_{20} values for GEP Model I (high–head gated conduit)

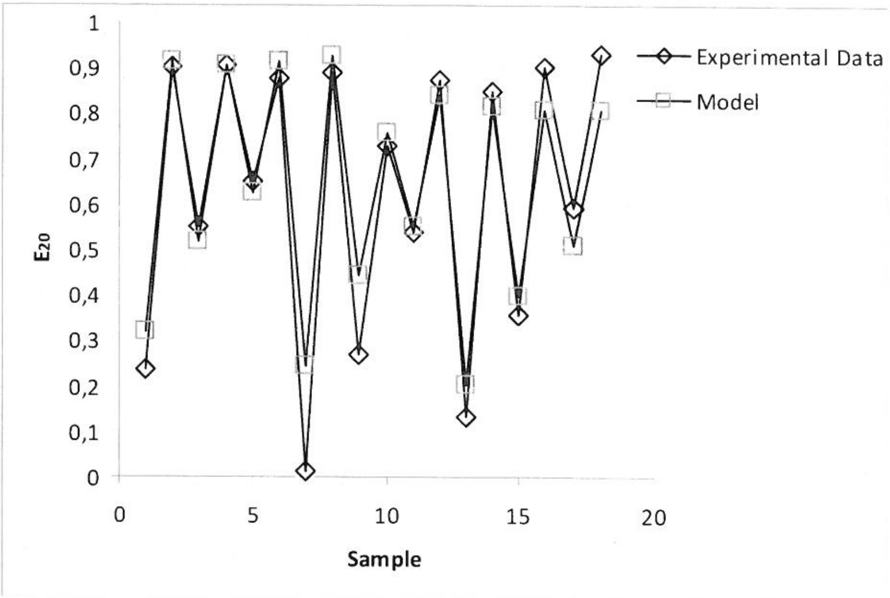

Fig. 6. The predicted and measured E20 values for GEP Model II (free–surface gated conduit)

CONCLUSIONS

This study investigates the capability of genetic expression programming (GEP) to predict oxygen transfer efficiency in high–head and free–surface gated conduits. The data for development and testing purposes are obtained from the experimental study. Two mathematical equations are generated from the GEP models. The sufficient agreement is found as results of the simulation procedures of the mathematical equations. The performances of models are questioned by some statistical performance criteria. The mathematical equations obtained from GEP Model I (for high–head gated conduit) and GEP Model II (for free-surface gated conduit), give high correlation coefficients and low MSE values. Consequently, the GEP approach can be widely applied to help resolve many problems in civil and environmental engineering. By using this approach, the time factor can be substantially reduced and human mistakes can be avoided.

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خوارزميات استدلال الثقة لشبكات التواصل الاجتماعي

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خلاصة

اكتسب التواصل الاجتماعي على الانترنت جاذبية كبيرة بين اوساط الشباب وشرائح المجتمع الاخرى من خلال مجموعة من التطبيقات مثل الرسائل الفورية ، المدونات، ومواقع شبكات التواصل الاجتماعي . ولكن يتسم هذا النوع من التواصل بعدم توفر وسائل كافية لتقييم مقدار الثقة التي يجب ان تعطى للمعلومات والاشخاص الذين يتم التعامل معهم من خلال هذه التطبيقات. يمكن لأنظمة المزكي ان تلعب دورا هاما في تقييم مصداقية المستخدم وتقديم توصيات تجاه إقامة صلات بين أعضاء الشبكة الاجتماعية. تهدف هذه الورقة لتحسين أنظمة المزكي القائمة على الثقة من خلال اقتراح خوارزمية جديدة وتعديل بعض خوارزميات القائمة. في هذه الورقة تم تقييم أداء أربع خوارزميات معدلة مع الخوارزمية الجديدة المقترحة لاستدلال درجة الثقة في المستخدمين باستخدام بيانات من موقع التواصل الاجتماعي تويتر. وأظهرت النتائج ان الخوارزمية المقترحة تقوم بتقديم توصيات دقيقة خاصة عندما تكون الشبكة الاجتماعية كثيفة.