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OPTIMIZATION OF CONSECUTIVE SIGNALIZED INTERSECTIONS BASED ON COMBINED ALGORITHMS – COMPARING RESULTS WITH MICROSIMULATION

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Abstract: The primary objective of this research is to optimize signal timing in consecutive signalized intersections. In this paper, the combination of genetic programming (GP) with genetic algorithms (GA) and neural network (NN) with genetic algorithm (GA) were used and compared in order to optimize signal timing in consecutive signalized intersections. First, genetic programming and neural network were constructed from existing signal timing data to predict the delay of intersections. Then genetic algorithm was applied to optimize these predictive networks (GP and NN). The results and comparisons of timing process and error percentage showed that neural network is more efficient than genetic programming. However, the ability of genetic programming in producing formula is a specific characteristic which makes it more applicable than neural network. Finally, for validating the results, Aimsun and Synchro micro simulation software were used, and accuracy of our models was approved.

Keywords: signal timing, signalized intersections, optimization, neural network, genetic algorithm, genetic programming.

1. Introduction

Increase in urbanization and creation of traffic density can result in emergent need for creating transportation system with maximum efficiency. Over the past years, traffic control has been considered as a basic problem in many cities especially metropolitans. Applying traditional solutions such as increasing infrastructures cannot be a suitable and desirable solution for meeting current traffic problems (Girianna and Benekohal, 2002). One of the main effective factors in urban traffic is signalized intersection. Increase in capacity and decrease in delay in these intersections can cause increase in total performance of the network (Adacher, 2012). Traffic signal systems have different types, which have been formed from simple system (the system uses predetermined data for purpose of setting fixed timing patterns) to sign adaptive controllers (the controllers work with the aim of optimizing sign scheduling in the network based on traffic status while occurrence). Traditional optimization methods are unable to find optimized answer. Mathematical models that estimate optimized green time have been simplified and hence, they can't be implemented for all conditions (Hu et al., 2015). For example, a model designed just for oversaturated conditions can't be

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applied under conditions of under saturated. In addition to mathematical models, many other models have been also presented based on simulation. The basic problem with these models is that they have no analytical basis and can use try and error for obtaining a suitable scheduling pattern (Hajbabaie et al., 2011; Dell'Orco et al., 2013). Such method has two main problems as follows: on one hand, achieving suitable answer is depended on engineering judgment and skill of the designer and there is no trust for being the best answer; on the other hand, the methods can't be applied for automated controlling systems.

Meta-heuristic methods such as genetic algorithm and neural networks, genetic programming or intelligent learning methods such as approximate dynamic planning can be significantly effective as an exact traffic simulation instrument for purpose of determining optimized scheduling of traffic signs in transportation networks (Alodat and Al-Odat, 2013; Zang et al., 2012). Genetic Programming (GP) is a branch of genetic algorithm. The main difference between genetic programming and genetic algorithm is presenting solution method in GP. The system is one of the newest and most applicable systems with evolutional processing performance (Konig, 2014). If it is possible for solving problem to use different formulations and equations, GP is in fact a system for creating and developing a solution for the problem. In GP, hundreds or thousands processing programs or formula would be produced genetically (Searson, 2009; Searson et al., 2010). The production would be conducted using Darwin's principles in the theory of Survival and evolution and with genetic combinational operators for intercross of formulas. Hence, GP is able to solve complicated problems using Method of Growth of Populations based on Darwinian Evolution and Mendelian genetics. Genetic algorithm is an intelligent search method, which has the ability to find an optimized answer among limited number of answers through generation.

2. Literature Review

One of the principle methods which is highly efficient in solving optimization problems is metaheuristic method (Teodorović et al., 2014). The first idea in formation of combined algorithms have been presented under a program with the title of OTSCS using artificial neural networks for purpose dynamic control of traffic sign. The program finds an optimized scheduling to minimize delay time in a two-phase single intersection. The mentioned program has been formed of two main parts. The first part is evaluation model of service level based on an artificial neural network and the second part includes a random optimization method, which is associated with service level evaluation. Obtained results indicate that if artificial neural networks are trained and designed in right way, combination of a random search method adapted with the network can be a good instrument for dynamic control of traffic sign (Abdullahi et al., 1999). Lo and Chow (2004) proposed a dynamic method in one-way arterial for optimizing signal timing. They used a cellular transitive model and simple genetic algorithm in order to optimize signal timing. They concluded that a flexible programming with variable green time and cycle length do not produce the best answer (Lo and Chow, 2004). By 1954, Genetic Programming was applied as an evolutional algorithm by Nils Aall Barricelli and for purpose of evolutional simulation. Since 1960 to early 1970, evolution algorithms were identified as optimization methods (Searson, 2009). By 1990, GP has been applicable mostly for simple problems because of its complicated calculation structure. Recently, GP has achieved brilliant and modern results in different research fields such as quantum calculations, electronic designing, and computer games classification and so on (Searson et al., 2010). Chang et al. (2010) proposed an optimization policy which was suitable for oversaturated intersections. Their method increased the efficiency of system through queue management. They tested their model on one over-saturated arterial with two intersections. The result showed this model increased the capacity of intersection and decreased average delay up to 22 percent (Chang et al., 2010).

3. Methodology

Based on HCM regulation, geometric status, traffic conditions and scheduling type of traffic signals can be the most effective factors in performance of traffic signals. In this regard, one can name basic parameters in phasing and scheduling traffic signs as follows: cycle length, green time, yellow time that is also known as changing time and also red time that is the time allowing the intersection to be discharged completely and type of phasing and sequence of phases (Highway Capacity Manual, 2000). Phasing variables are in form of determining simultaneous movements, sequence and their implementation. Right turn movement would be conducted usually with direct movement; although left turn movement can be predicted in form of protected, unprotected and a combination of the two modes.

At the first step, it would be necessary to take geometric conditions (including type of zone, number of lanes, average lane width and slope) and then, traffic conditions (including density of vehicles in each approach and finally origin-destination matrix in peak hour) in the network should be estimated. Finally, conditions of traffic signal should be determined at the current situation on peak hours (including cycle length, green time, the time between two greens, yellow time in addition to all red time and schedule of fixed and changing mode of signals). The network at the current situation would be modeled in Synchro Software and average delay would be obtained under such conditions.

At the next step, existing schedules would be expanded using Synchro software. For this purpose, duration of different cycles for intersections would be applied in certain period and also different phasing modes would be considered for intersections (in form of protected left turn, unprotected and combination of both modes). Through considering all possible modes for the desired intersections, delay would be estimated for each mode separately. Afterwards, set of provided statistics would be applied for purpose of training neural network and formation of genetic programming network. Manner of training neural network is in such manner that phasing and scheduling variables would be introduced as input layer nodes of neural network and in output layers, delay would be considered as the criterion for efficiency of whole network. Input layer in neural networks is a layer, in which training set would be applied for purpose of training the network and the layer can be in fact considered as the gate of the network. Output layer is the last layer of the neural network and it can be considered as one of the most important layer of the network, as desirable outputs are needed. In fact, outputs of the network, which are delay times in this study, would be produced in this layer and would be then compared to desired outputs. Propagation-Backward algorithm can arrange hidden layers through propagating output error in layered form to the backward and through regulating weights in each layer. Hence in a backward network, hidden layers can form main core of calculations and these layers can receive inputs from input layer using neurons and then, they produce amount of output in output layer. Each intersection would be scheduled separately and would be investigated under different schedules of whole network and delay can be estimated through this. Following, all collected data in previous steps would be analyzed using genetic programming with Multigene Symbolic Regression (MSR) and delay would be estimated through this. In genetic programming, there is no need for effective data because of nature of the system and using evolution theory. In fact, regression method of the system is in such manner that it uses some data during the analysis that create minimum error in estimations. As a result, using more data can cause empowerment of the schedule and minimization of errors.

In Multigene Symbolic Regression for input data, the primary population would be created using genetic programming, in which each individual includes several trees that their numbers can be determined. Then, minimum square of errors method would be applied for purpose of determining weight of each tree and fixed value in each formula. Afterwards, error level of each equation would be determined using competency function and the new population would be produced using the mentioned operators. The algorithm goes ahead in iterated mode based on the mentioned process. Final conditions and exiting from algorithm cycle is achieving determined number of population or the desired error level. In fact, in each cycle of population production, the best formulation with the lowest error can be considered as the solution for the problem. Manner of performance of genetic programming (GP) and neural network (NN) is as follows: firstly, the network would be trained by 70% of collected data from intersections with different schedules applied on them and then it would be validated with the remained 30% of the data. The data are same different durations of the cycle, along with different phasing modes, which can be obtained from statistical background of the network under different scheduling conditions. At the final step, genetic algorithm would be applied for purpose of investigating optimized values for estimator networks to achieve minimum delay rate. Optimization would be performed on GP and neural network. Based on structure of genetic algorithm that was mentioned before this, in each step of implementing algorithm, there is a part as evaluation of efficiency index, in which value of target function would be obtained based on produced variables with genetic algorithm.

Desired efficiency index in this study is total delay of the network, which has been estimated using neural network and genetic programming. Therefore, the mentioned network would be called regularly and desired inputs of genetic algorithm would be entered to it to estimate its competency. Genetic algorithms include 3 steps of coding answer, determining parameters of genetic algorithm implementation of genetic algorithm. Scheduling variables applied for training genetic programming play role of genetic algorithm's genes, which can be illustrated using paired coding method programming process of neural network, genetic programming and implementation of genetic algorithm would be conducted using developed codes in MATLAB software. Finally, obtained results from optimized network by combination of genetic programming with genetic algorithm and also neural network with genetic algorithm would be compared in Synchro software. Finally, created signal timing by combined algorithms and optimize signal timing produced by Synchro software have been simulated in AIMSAN software for purpose of validation.

4. Case Study

For purpose of modeling, two adjacent intersections (Dadman-Farahzadi and Dadman-Darya) have been selected, which have normal and regular forms. In terms of location, they have been located in a place with considerable traffic density. As the algorithm considers no separated phase for passengers, density of the passengers should not be high and should cause no disruption for movement of vehicles as it is illustrated in Fig. 1.

Fig. 1.
The Map of Location of Intersections

4.1. Data Collection

In order to obtain Origin-Destination (O-D) matrix, data collection of traffic flow has been conducted in the peak hour. It has been depicted in Table 1.

Table 1
Illustration of Movement Volume between Origin and Destinations in Dadman-Farahzadi and Darya-Farahzadi Intersections PCE/h = Passenger Car Equivalent per Hour

	South Farahzadi	East Dadman	East Darya	North Farahzadi	West Dadman	West Darya
South Farahzadi	128	125	112	599	298	195
East Dadman	620	7	41	190	1290	63
East Darya	301	77	187	299	125	330
North Farahzadi	606	250	570	300	160	584
West Darya	129	33	565	199	42	0
West Dadman	188	655	53	281	85	69

Currently, Farahzadi-Dadman intersection has controlled by preset fixed timing signal in 4-phase form. Farahzadi-Darya intersection has controlled by preset fixed traffic signal in 3-phase manner. Green sign and red sign time in Farahzadi intersection with Dadman and Darya boulevards in peak hour have been respectively presented in Table 2 and Table 3.

Table 2

Timing of Traffic Signs in Farahzadi-Dadman Intersection

Phase Number	Name of Approaches	Red Time (s)	Green Time (s)
1	Farahzadi to North, East and West	121	34
2	Farahzadi to South, East and West	114	41
3	Dadman to West, North and South	119	36
4	Dadman to East, North and South	123	32

Table 3

Timing of Traffic Signs in Farahzadi-Darya Intersection

Phase Number	Name of Approaches	Green Time (s)	Red Time (s)
1	Farahzadi to North,East and West	42	111
2	Darya to East, West,North and South	53	100
3	Farahzadi to South,East and West	49	104

4.2. Applying Different Timings for Intersections

Using collected data in the previous section, the proposed model in the current situation has been modeled in Synchro software and total delay in the network has been estimated. Afterwards, new timing and phasing modes would be applied for intersections in certain limitation and mean value of whole network delay would be estimated for each mode. Timing variables include cycle length and green rate, which cycle length would be considered variable between 150 and 200 seconds. Percent of green time that is specified to east-west approaches would be varied to 40%, 50% and 60%. For phasing mode, 12 approaches are existed in each intersection as follows: East Base Left turn approach (EBL); East Base Through approach (EBT); East Base Right approach (EBR); West Base Left approach (WBL); West Base Through approach (WBT); West Base Right approach (WBR); North Base Left approach (NBL); North Base Through approach (NBT); North Base Right approach (NBR); South Base Left approach (SBL); South Base Through approach (SBT); South Base Right approach (SBR). Now through considering protected left turn, unprotected left turn or a combination of both of these mode, different situations can be created for the two intersections. In general, 162 modes have been created for the network including two consequent intersections. For this purpose, firstly existed timing modes would be developed using Synchro software and then obtained statistics would be applied for purpose of training NN and GP.

4.3. Estimating Delay Rate Using Neural Network

In this section, all obtained data from modeling have been analyzed using multilayered neural network program and delay rate has been estimated. For purpose of estimating by neural network, multilayer neural network in MATLAB software with basic order of newfit has been applied.

In the program with try and error and investigation of different values and modes, it has been selected as the best mode for approximation in neural network, as a result of which for back-propagation network training function, Levenberg-Marquardt backpropagation function has been applied; for backpropagation weight/bias learning function, Gradient descent with momentum weight and bias learning function has been applied; for performance function, Mean squared normalized error performance function has been applied; for transfer function in hidden layers, Hyperbolic tangent sigmoid transfer function has been applied; for Transfer function for output layers, linear function has been applied; for number of layers, 20 layer and for number of neurons, 10 neurons have been applied.

In order to evaluate performance of estimation and prediction models, different performance indices are existed such as MSE, which is mean square error and can be calculated based on Eq. (1). One can also refer to RMSE, which has been estimated in Eq. (2).

$$\mathrm{MSE} = {}^{1}\!/_{m} \sum_{i=1}^{m} (E_i - e_i)^2 \tag{1}$$

$$RMSE = \sqrt{{}^{1}\!/_{m} \sum_{i=1}^{m} (E_i - e_i)^2} \tag{2}$$

Where; m refers to tot number of data; E is equal to exact value of output and e refers to output of network (2).

For purpose of approximation of 162 data, 70% of data have been considered as training data and 30% of them have been considered as experimental data. Based on presented modeling, mean squared errors for all data has been equal to 133. In Fig. 2, the diagram indicates error levels of training and examining in 17 iterations.

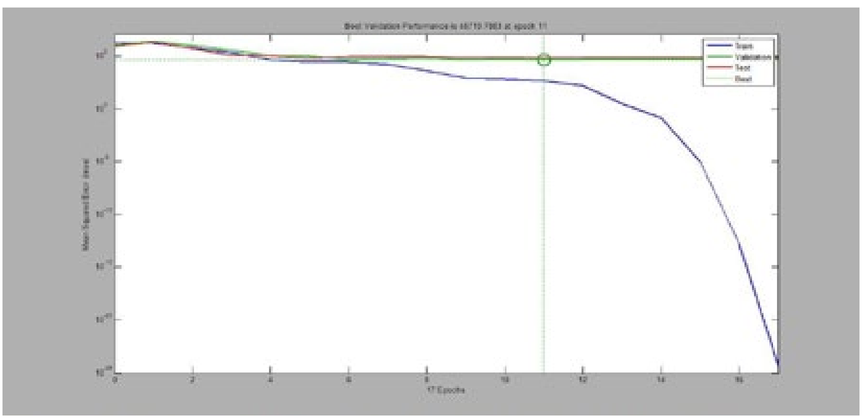

Fig. 2.
Diagram of Mean Squared Errors for Training and Examining in Neural Network

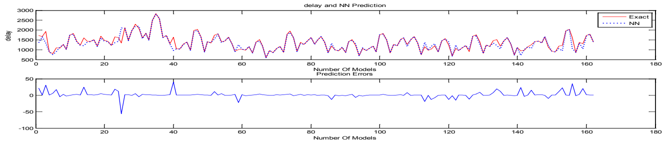

Fig. 3.
Comparing Actual Values and Predicted Value by Neural Network

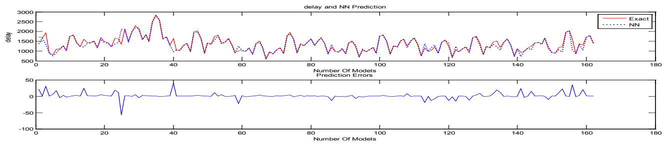

Fig. 4.
Error Percent Diagram by Neural Network

In Fig. 3, predicted delay values by neural network have been compared to output values of the software. Blue curve illustrates predicted delay rate by neural network and red curve indicates calculated values by the software. The diagram in Fig. 4 has also illustrated error percent of the network.

4.4. Approximating Delay Rate Using Genetic Programming

All obtained data from the previous step have been analyzed using GP through Multigene Symbolic Regression and delay rate has been estimated. In GP, because of nature of the system and using evolution theory, there would be no need for determining effective data. Based on the data, 26 inputs have been defined for the program and one output has been obtained from the program that is same delay rate. Accordingly, value of inputs in GP network is introduced equal to 26 inputs, which is according to inputs of the program based on Table 4 and Table 5.

GP algorithm would be stated as the primary population through random production. The formulas include functions, variables and fixed coefficients. Applied functions in the equations can be in different forms such as simple calculative operators; mathematical standard functions; conditional functions or logical functions. Due to the type of problem, equations can include numerical, conditional, logical, actual, vector and symbolic values or they can be multi-valued.

Table 4
Inputs of Genetic Programming in Dadman-Farahzadi

Dadman-Farahzadi												E-W Ratio	Cycle Length
SBT & L	SBT	SBL	NBT & L	NBT	NBL	WBT & L	WBT	WBL	EBT & L	EBT	EBL		
X14	X13	X12	X11	X10	X9	X8	X7	X6	X5	X4	X3	X2	X1

Table 5

Inputs of Genetic Programming in Darya-Farahzadi

Darya-Farahzadi												E-W Ratio	Cycle Length
SBT & L	SBT	SBL	NBT & L	NBT	NBL	WBT & L	WBT	WBL	EBT & L	EBT	EBL		
X26	X25	X24	X23	X22	X21	X20	X19	X18	X17	X16	X15	X2	X1

In order to estimate average delay, due to the type of data, different networks were created, so that effective parameters in the network can be determined in improving approximation. Number of gene, depth of each tree and also rate of primary population and number of generation have been the most important effective factors in approximation of the network. On the other hand, over magnification of the produced equation can cause it to have inadequate use. Hence, after repetitive modeling modes in form of try and error, primary population has been considered equal to 100 people and number of generation period has been considered equal to 1000 periods. Applied functions include sinus, cosinus, and tangent, hyperbolic and symbolic function. Number of genes is equal to 10 and depth of trees has been considered to 10. For purpose of approximating 162 data, 70% of data have been considered as training data and 30% of them have been considered as experimental data. Data and output of the program have been presented in Table 6.

Table 6

Summary of Values and Outputs of Genetic Programming

10	Max genes	100	Population size
116.64	Training RMSE	1000	Number of generations
190.82	Testing RMSE	10	Max tree depth
1156.20	Time computing (sec)	Inf	Max nodes per tree

In Fig. 5, values of RMSE for predicted values have been traced based on GP. The upper diagram has illustrated RMSE in logarithm mode. In Fig. 6, RMSE values have been illustrated in the diagram in simple form. As it is obvious, after generation 300, reduction of error level has too mild slope.

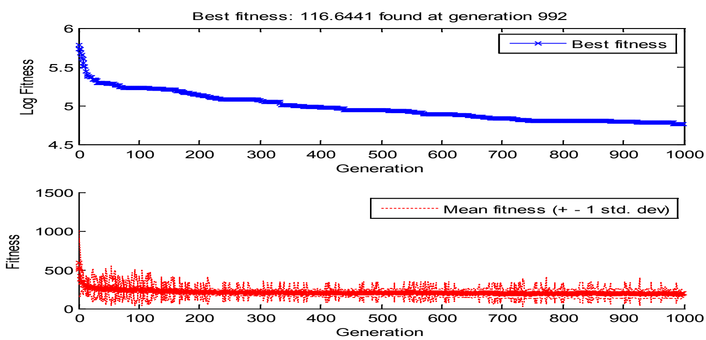

Fig. 5.

Diagram of Error Level while Training for 1000 Generation Periods (in Logarithm Form)

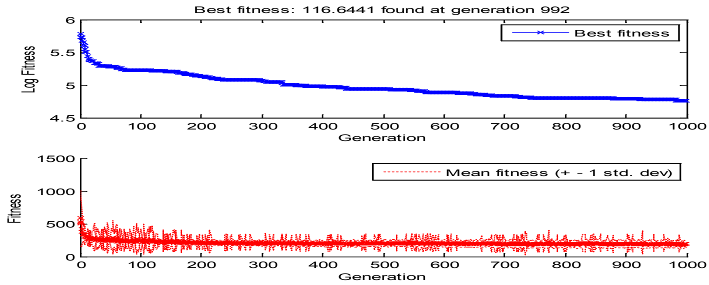

Fig. 6.
Diagram of Error Level while Training for 1000 Generation Periods (in Simple Form)

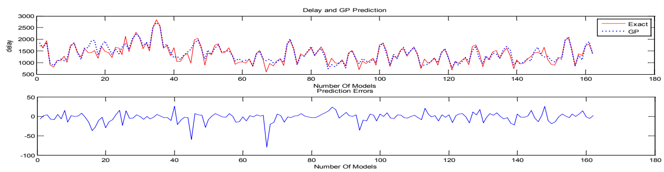

Fig. 7.
Diagram of Comparing Actual Values with Approximate Values for All Data

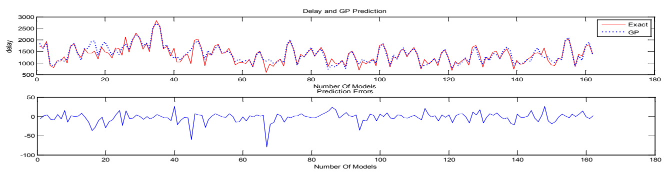

Fig. 8.
Diagram of Error Percent for All Data

In Fig. 7, predicted values by GP have been compared to outputs of the software. In the Fig. 8, error percent of predicted values by GP have been also traced. In Fig. 9 and Fig. 10, predicted values by GP in training and experimenting modes have been traced separately and also RMSE value has been also depicted in the top of each diagram. Clearly, RMSE values in training are significantly lower than experiment.

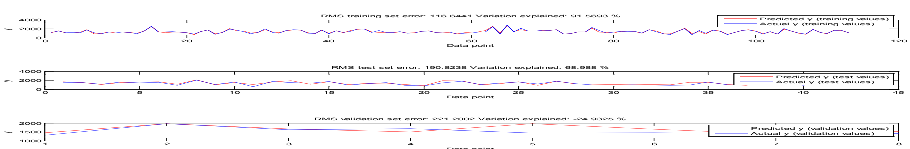

Fig. 9.
Diagram of Comparing Actual Values with Approximate Values for Training Data

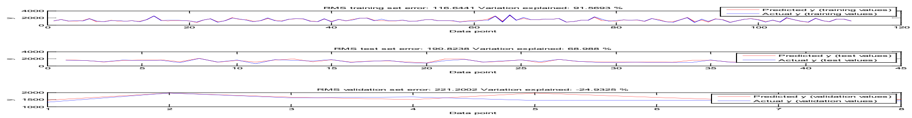

Fig. 10.
Diagram of Comparing Actual Values with Approximate Values for Experimental Data

In Fig. 11, coefficient rate of each gene (tree) has been depicted in final equation of GP. Through comparing weights of each gene, in fact percent of participation of each gene in final equation can be observed. Genes 1, 2 and 7 have the most share in the final equation.

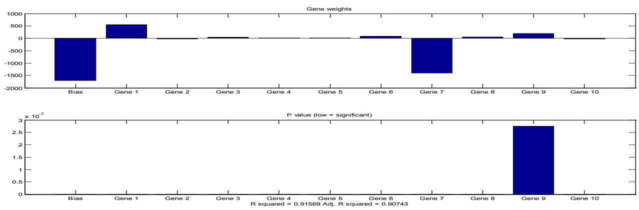

Fig. 11.
Diagram of Illustrating Weight of Each Gene in the Presented Equation in GP

4.5. Presenting Generated Equation by GP

In this section, generated equation by the GP has been presented for each gene separately. As it is obvious, GP has generated 10 genes, which the maximum depth in each gene has been considered to 10. Gene 1 to Gene 10 indicate 10 generated genes by the GP.

Eq. (3) indicates final equation of GP, which is in fact set of all expressed genes and total set of all Genes (Genes 1-10).

Gene 1=554,1 plog(x^8)-1709,
Gene 2= -(569(x^10-1,0x^9+plog(cos(psqroot(x^1)))+(plog(psqroot(x^10-x^2-psqroot(x^17))))))/20
Gene 3=45,18 x^11-45,18 psqroot(plog(cos(x^1+x^16-plog(x^5)))) -45,18 psqroot(plog(cos(x^1+x^19-plog(x^8))))-45,18plog(cos(x^10-psqroot(x^17)))
Gene 4=16.22 x^13-16,22 psqroot(psqroot(x^10-x^19-plog(psqroot(x^10-x^2))))-16,22cos(x^1+x^4-cos(x^1+x^19-x^8))-16,22 plog(cos(psqroot(x^1)-x^17))
Gene 5=10,43 plog (cos(x^1+x^4-cosx^1+x^19-plog (x^8))))-10.43x^19
Gene 6=88,36x^2-88,36 psqroot (x^2-x^8)
Gene 7=1399(psqroot(psqroot(x^5))-1,0 plog(x^8))
Gene 8=54(x^10-1,0 psqroot (x^17))
Gene 9=192,5 cos(plog(x^5)-cos(psqroot(x^5)-psqroot(x^19-x^11))))
Gene 10=21,63(x^1-1,0 x^14+plog(x^(12/319)-cos(x^24)

"Y=25,55x^10-21,63x^1+45,18x^11+16,22x^13+21,63x^14-10,43x^19+88,36 x^2+28,45x^9-88,36 psqroot(x^2-x^8)-21,63plog(0,003127x^12-cos(x^24))+1399,0psqroot(psqroot(x^5))+10,43 plog(cos(x^1+x^4-cos(x^1+x^19-plog(x^8))))-16,22psqroot(psqroot(x^10-x^19-plog(psqroot(x^10-x^2))))-16,22 cos(x^1+x^4-cos(x^1+x^19-x^8))+192,5cos(plog(x^5)-cos(psqroot(x^5)-psqroot(psqroot(x^19-x^11))))-28,45plog(cos(psqroot(x^1)))-28,45plog(psqroot(x^10-x^2-psqroot(x^17)))-45,18 psqroot(plog(cos(x^1+x^19-plog(x^5))))-45,18psqroot(plog(cos(x^1+x^19-plog(x^8))))-844,9 plog(x^8)-54,0psqroot(x^17)-16,22 plog(cos(psqroot(x^1)-x^17))-45,18plog(cos(x^10-psqroot(x^17)))-1709,0 (3)

psqroot(a)=√(|a|)

plog(loga)=log|a|

4.6. Comparing Neural Network and GP

Here, results of neural network and GP have been compared to each other in summary.

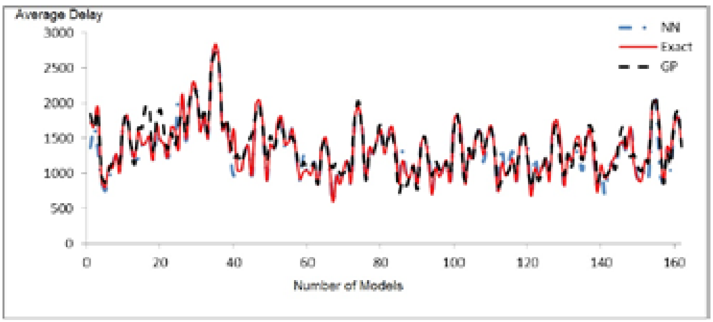

Fig. 12.
Comparing Results of NN and GP

As it is obvious in diagram of Fig. 12, predicted values by the neural network and GP have desirable approximate.

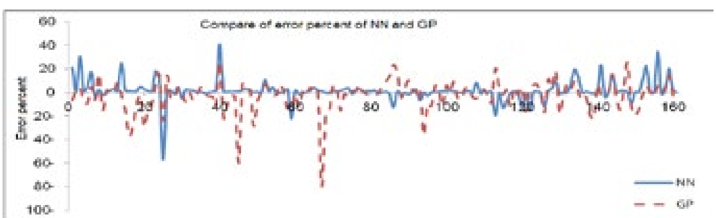

Fig. 13.
Comparing Error Percent of NN and GP

In diagram of Fig. 13, values of error level of neural network and GP have been compared to each other. As it is obvious in the diagram, in some points both programs have high error level; although in some points one of the programs has lower error level than the other one. In general, neural network has lower error level than GP and this issue has been presented in Table 7 in summary.

Table 7
Comparing Neural Network and Genetic Programming

Minimum error percent	Maximum error percent	Calculation time	RMSE	Program
0.00245%	56.89%	328s	133.36	NN
0.0528%	79.57%	1156s	145.37	GP

As it is depicted in Table 7, generally in terms of both time of calculations and error level, neural network is in better situation than GP. However, presenting the formula by the GP is a brilliant feature of the network that can have better use than neural network.

4.7. Determining Values of Optimized Inputs

Optimization has been conducted on both systems of NN and GP. In order to conduct optimization, "ga" base order in MATLAB software has been applied. Primary population rate and generation rate has been equal to 1000. Due to the presented optimized model by engineering software of Synchro, number of variables would be equal to 10 and all remained variables would be 0. As the answer of the problem can't be negative, this issue can be considered as limit of optimization problem. In addition, due to this issue that parameters are in form of integers, this issue should be also considered in the program. For this purpose, before entrance of variables to the target function that is same approximate network, they should be entered to the target function in form of integer and round up. Through this, obtained values by genetic algorithm would cause minimization of target function through becoming round up. Values of the current and optimized status of engineering software have been given to the two approximate networks (GP and NN) and obtained results have been compared to outputs of the software in Table 8.

Table 8
Comparing Calculated Delay Obtained from Software (SYNCHRO) and Two Approximating Networks (GP and NN)

Error percent of GP	Error percent of NN	Delay calculated by GP & GA	Delay calculated by NN & GA	Delay calculated by SYNCHRO	
9.97%	8.64%	1361.44	1131.07	1238	Current Situation
6.18%	2.72%	1252.93	1223.93	1180	Optimized Situation

4.8. Validation of Proposed Algorithms and Investigation of their Impacts on other Parameters

For purpose of comparing proposed methods in terms of traffic index, the mentioned methods have been simulated in AIMSUN software. It should be mentioned that the software has been also applied for purpose of analyzing the current situation. In continue, methods would be compared and evaluated based on different outputs of the software.

Finally, changing levels in traffic of the desired network in each method would be presented based on the current situation.

In Table 9, changing levels of traffic parameters have been estimated based on the current situation.

Table 9
Changing Level of Traffic Parameters Based on the Current Situation

	Flow	Density	Speed	Delay	Stop Time	Travel time
Current Situation	6450	49	7	554	461	299519
NN & GA	6672	45	8	458	363	242633
GP & GA	6679	52	11	553	459	236296
SYNCHRO	6996	51	12	487	487	328558

In Fig. 14, ranking of the proposed methods has been estimated in terms of imposed delay on the vehicles. Naturally, the method with less delay would be more desirable than others. Therefore, the most desirable method in terms of delay can be combination of NN and GP that have the minimum delay rate.

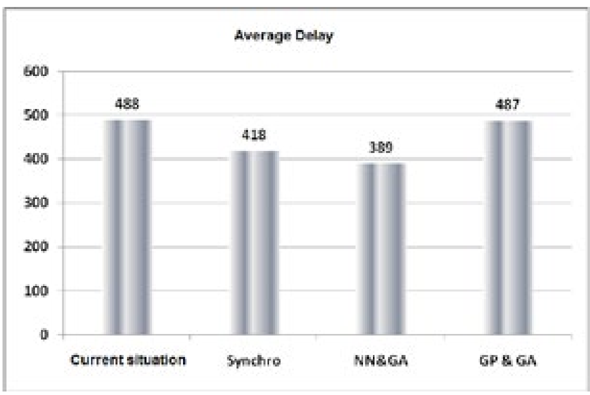

Fig. 14.
Ranking Different Timing Methods in Terms of Imposed Delay on Vehicles

Ratio of flow to density indicates smooth flow of traffic in the network. The more the movement flow in the network is, the better performance of the network would be and it would have higher capacity of movement of vehicles per hour and vice versa, the less the density of the network is, the better performance of the network would be. Hence, the bigger the ratio is, the higher desirability of the network would be. In Fig. 15, ranking of proposed methods has been presented based on flow to density ratio. According to the figure, in the combination of NN and GP, the network has the highest moving flow to density ratio.

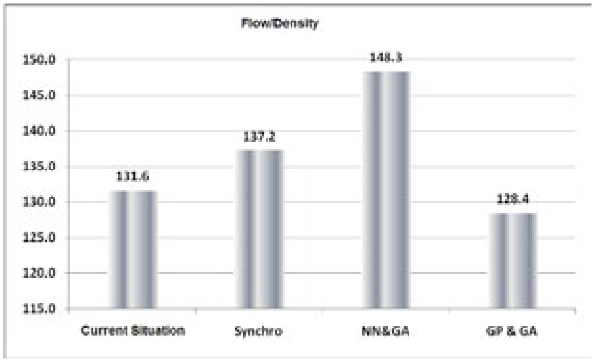

Fig. 15.
Ranking Different Timing Methods in Terms of Flow to Density Ratio in Vehicles

Theoretically, every network that has lower travel time is more desirable in terms of traffic and vice versa, the more the speed of cars is in the network, the network would be more desirable in terms of traffic. On the other hand, in this software, travel time of those vehicles would be calculated that have been excluded from the network. Therefore, in those networks that have been blocked and vehicles have not been able to pass the network, less travel time has been obtained and this can't be sign of desirability of the network. Hence, travel time to speed of cars ratio has been applied for purpose of evaluating models. Hence, the less the ratio is, the higher desirability of the network would be. In Fig. 16, ranking of proposed methods has been presented based on travel time to speed ratio.

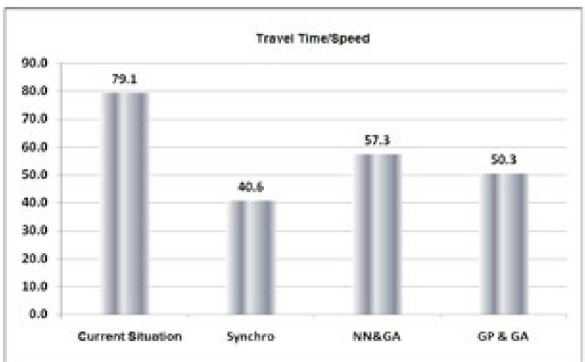

Fig. 16.
Ranking Different Timing Methods in Terms of Travel Time to Speed Ratio

5. Conclusion

Evaluation of outputs of combined algorithm of NN and GP and comparing it with outputs of SYNCHRO software has been conducted using AIMSUN software. Other results obtained from the study due to the conducted analyses on statistics and obtained results from model implementation are as follows:

1. Presented methods have been to some extent successful in regard with achieving their target that is determining optimized timing. Therefore, it could be mentioned that the methods can depict relative improvement compared to existed methods of SYNCHRO software and HCM regulation.

2. Artificial neural networks and genetic programming have had desirable performance in regard with predicting average delay imposed on vehicles under different timing combinations. The method has presented desirable answers for two studied intersections.

3. In general, both in terms of calculation time and error percent, neural network has better situation than genetic programming. However, presenting equation by genetic programming can be a brilliant feature of the network that can have better use than neural network.

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