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# Evaluation of Local Compression Capacity of Stirrups-Confined Concrete using Genetic Programming

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**Abstract:** Local compression capacity of stirrups-confined concrete is considered as a local zone in load transfer in many structural applications such as the post-tensioned restressed concrete bearing area or at end bearings of bridges. This article offers an applicable computational equation to evaluate the local compression capacity of stirrups confined concrete. A machine learning model based on multi-gene genetic programming is utilized to formulate the proposed formula. A database consisting of data collected from previous literature is used in discovering the correlation between the input parameters with compression capacity of stirrups-confined concrete. The numerical study covers the use of both ordinary and high-performance concrete, since the peak strength of concrete prisms varied from 16 MPa to 112 MPa. It takes into account the bearing area aspect ratio and stirrups confined core area aspect ratio. The ratio of duct diameter to section width is varied from zero which means no duct to 0.29. The effect of stirrups is undertaken with both the yield strength of stirrups, and the volumetric ratios.

**Keywords**: Multi-Gene Genetic Programming; concrete, Compression Capacity; Stirrups-Confined Concrete; Prestressed Concrete; Artificial Intelligence

## 1. INTRODUCTION

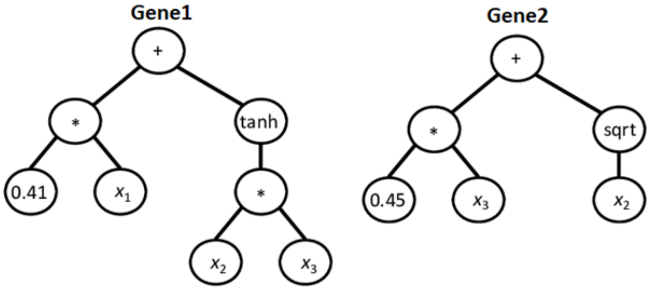
Local compression capacity of stirrups confined concrete (LCCSCC) is considered as an important issue to ensure safety and integrity of many structures that have concentrated load acting directly on a relatively small area. As an example of such conditions, LCCSCC can be found as a solid section in building columns bearing on concrete pedestals, and bridge bearing on the concrete piers. It can also be found as a hollow section in anchorage zone in post-tensioned concrete members and the joints of the precast columns. At LCCSCC zone, a large concentration of compressive stresses is transmitted into concrete by the concentrated load and then spreads transversely until there is a more linear stress distribution throughout the whole member section.

Due to the composite nature of concrete and reinforcement, accurate prediction of its behavior is challenging. Relying solely on mechanics to precisely evaluate its performance is not available most of the time. So, Latest researches have used genetic programming and its more powerful variant (multi-gene genetic programming (MGGP) to predict many of its properties like concrete creep [1,2], the bond strength of near-surface-mounted FRP bonded to concrete[3 ], shear strength of steel fiber reinforced concrete beams [4,5], shear-strength prediction of squat reinforced concrete walls [6], and the extent of reinforced concrete's damage caused by steel corrosion[7]. In this study, Multi-Gene Genetic Programming (MGGP) to uncover the complexity of LCCSCC is adopted.

### Multi-Gene Genetic Programming (MGGP) Model

Genetic programming (GP), like other artificial intelligence systems, has the potential to solve problems without the need for outside assistance to instruct the computer on how to do so[8].A machine learning technique called genetic programming (GP) uses biological inspiration to evolve computer algorithms to carry out a task. To achieve this, a population of computer programs (represented as tree structures) is generated at random, and the best-performing trees are then mutated and crossed over to produce a new population. Iterations of this process are carried out until the population contains programs that effectively solve the job [9]. One or more genes that each have a "conventional" GP tree make up a multigene MGGP.

**Error! Reference source not found.**1 shows how MGGP can define and correlate variables in nonlinear ways where, the shown two trees (Genes) have non-linear terms (**Tanh** and **square root**). However, the shown model is linear in the parameters with regard to the coefficient $d_0$, $d_1$ and $d_2$. Subsequently, MGGP combines the advantage of classical linear regression with the capability to represent non-linear behavior [10].




$$y = d_0 + d_1(0.41x_1 + \tanh(x_2x_3) + d_2(0.45x_3 + \mathrm{sqrt}(x_2))$$

Fig 1: Example of a Multi-gene Symbolic Model

Numerous individuals that were randomly created from the initial population are included in the population. As the GP algorithm progresses, the individuals are subject to some evolutionary operation. The mean fitness of the people as well as the fitness of the best individuals improves as the GP algorithm continues to run.

The likelihood of selection in the selection operator increases with fitness. For the same number of choices, this is repeated several times. Fig 2 shows the GP's organizational structure.

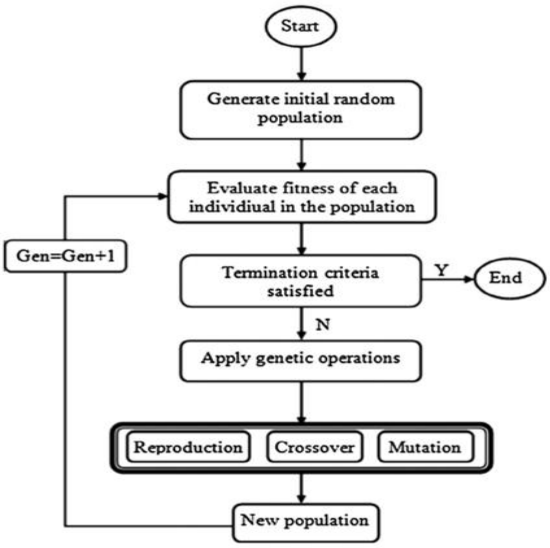



Fig 2: Flow Chart of Genetic Programming [11]

**Model inputs and outputs**

The 180 data points used in this study are obtained from the literature [12]. Then, the data is preprocessed and increased to be 1991 points. Data extrapolation is done by adding 9 points between any two successive points. By dividing the space between the two succeeding points evenly, new points are added. The created intermediate points aim to enrich the calculations and to give the MGGP the ability to properly predict the correlation between the inputs and the output.

Fig 3 shows a sample graphical presentation of local compression capacity of stirrups confined concrete elements. The sample represents the local concentration of stresses associated with post tension pre-stressing. Other cases include, but not limited to, frame hinged supports, bridge bearings…etc. **Error! Reference source not found.** illustrates a description of the input and output parameters used to develop the MGGP models. Table 1 shows the data range of inputs and outputs used to build the MGGP model.

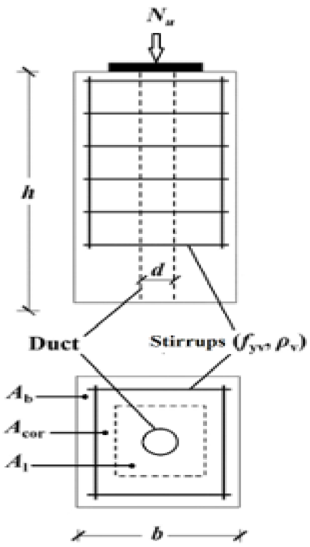



Fig 3: Graphical Presentation of Local Compression Capacity of Stirrups-Confined Concrete Elements.

*Where, $A_b$ is the gross supporting area; $A_l$ is the area of the bearing plate; $A_{cor}$ is the area confined by stirrups; $d$ is duct diameter; $b$ is section width of the specimens; $f_{yv}$ is the yield strength of stirrups, and $\rho_v$ is the volumetric ratio of the stirrups.*

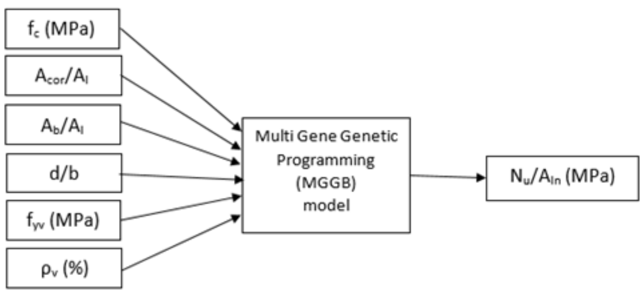



Fig 4: Inputs and Output Used for Constructing MGGP Model

The data points are separated at random into three groups: the training data (1391 points), the testing data (300 points) and the validation data (300 points). Using training data, the tree shape structure and quantity are automatically evolved during a run. After the run, testing data can be utilized to assess the improved models. The testing data is only used to determine how well a model generalizes to new data, not to alter the models themselves. To help prevent over fitting, the validation data set can be supplied,[13].

Table 1: Inputs and Output Parameters with Their Range of Variation

| Parameters type | Description | Variation range | | |
|---|---|---|---|---|
| | | Min. | Max. | Mean |
| Input | $X_1 = f_c$ (MPa)<br>The peak compressive strength of concrete prisms | 15.6 | 112.3 | 33.9 |
| | $X_2 = A_b/A_l$<br>The bearing area aspect ratio | 1.36 | 17.29 | 4.6 |
| | $X_3 = A_{cor}/A_l$<br>The stirrups confined core area aspect ratio | 0.18 | 12.7 | 2.62 |
| | $X_4 = d/b$<br>The ratio of duct diameter to the section width | 0 | 0.29 | 0.062 |
| | $X_5 = f_{yv}$ (MPa)<br>The yield strength of stirrups | 233 | 660 | 388 |
| | $X_6 = \rho_v$(%)<br>The volumetric ratios of confining stirrups | 0.33 | 10.6 | 2.72 |
| Output | $Y = N_u/A_{ln}$ (MPa)<br>Local compression capacity of stirrups confined concrete | 30.67 | 383 | 103.7 |

**Developing Mathematical Model**

In order to apply MGGP, the study employs GPTIPS which is an open-source MATLAB based software platform for symbolic data mining (SDM) that uses the MGGP as the engine driving the automatic model discovery process [14]. The mathematical formulation accomplished in this study by using GPTIPS with MATLAB2017b software. The MGGP technique needs numerous parameters which are selected after doing many investigative runs of GPTIPS toolbox and assessing the performance state. The parameters used in this study are summarized in **Error! Reference source not found.**.

MGGP is an iterated method. The total number of iterations is approximately equal to the "number of generation" multiplied by "population size" with some reduction due to the repetition of elite individual. The more iterations GPTIPS achieves, the more precise the resultant equation has. While increasing the "number of genes" and the "tree depth" directly increase the complexity level of the resultant extracted equation.

Table 2: Parameters Setting for the MGGP

| **Parameter** | **Value** |
|---|---|
| Population size | 800 |
| Number of generations | **50** |
| Number of runs | 1 |
| Parallel mode | Off |
| Tournament type | Regular |
| Tournament size | 10 |
| Elite fraction | 0.15 |
| Fitness cache | Enabled |
| Lexicographic selection | True |
| Max tree depth | 3 |
| Max nodes per tree | Inf |
| Using function set | TIMES, MINUS, PLUS, RDIVIDE |
| Number of inputs | 6 |
| Max genes | 7 |
| Constants range | [5 20] |
| Complexity measure | Expressional |

The extracted Simplified overall MGGP equation obtained from the procedure is shown as follows:

$$N_u/A_{1n} = 1.707\ X_1 + 1.707\ X_2 + 11.97\ X_3 + 7.167\ X_4 - 4.803\ X_6 - 4.803\ X_1 X_4 + 1.587\ X_2 X_6$$

$$+ 1.707\ X_3 X_6 + 0.2401\ X_4 X_5 + 0.01842\ X_1 X_6^2 - 0.0003125\ X_2^2 X_5 X_6 - 9.513$$

Where, $X_1$ --- $X_6$ are identified in table (1)

**Statical properties of multigene model for training data**

Fig 5 illustrates that the MGGP consists of seven genes and display the weight of every gene and bias. The summation of all genes and bias term is forming the final equation.

```
Gene 1 and bias term:
0.2401 x4 x5 - 9.513

Gene 2:
- 4.803 x4 - 4.803 x6 - 4.803 x1 x4

Gene 3:
11.97 x3 + 11.97 x4

Gene 4:
                    2
-0.0003125 x2   x5 x6

Gene 5:
                    2
0.01842 x1 x6

Gene 6:
1.587 x2 x6

Gene 7:
1.707 x1 + 1.707 x2 + 1.707 x3 x6
```

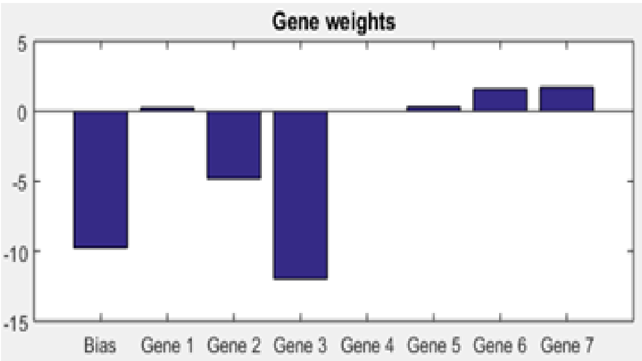



Fig 5: Bias and Gene Weights

**Error! Reference source not found.** illustrates that all genes have a significant influence on the $Nu/A_{ln}$.

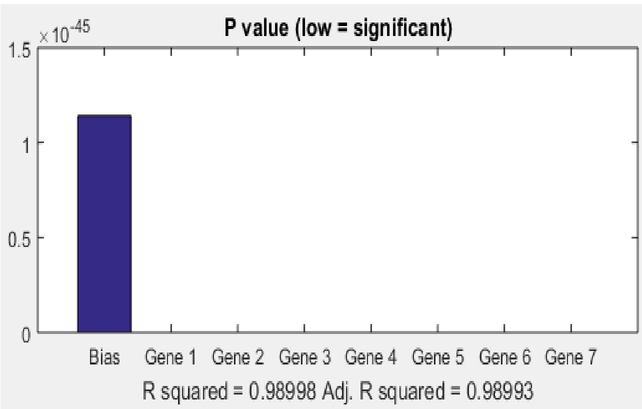



Fig 6 :P-Values of Model Genes (on training data)

The detailed performance is assessed point by point for training, test, and validation data points as shown in **Error! Reference source not found.**. The model prediction of individual ensures the good fitness behavior with R2 reaches 99%. The predicted y and actual y are almost similar.

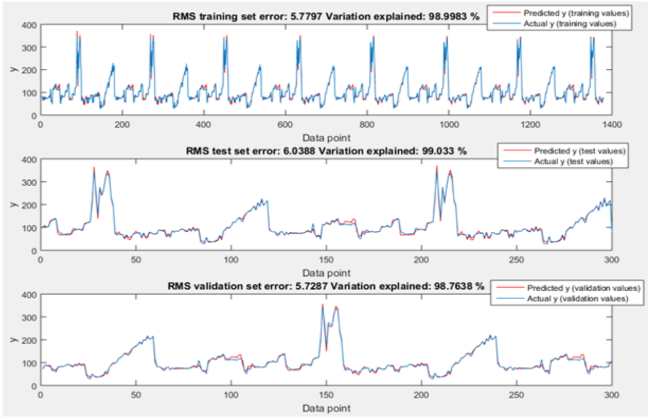



Fig 7: Multigene regression, Model Prediction of Individual

Fig 8 illustrates the predicted concrete compressive strength vs actual concrete compressive strength as scatter plots. The root mean square error for the three data groups are given and show a high accuracy of the extracted equation.

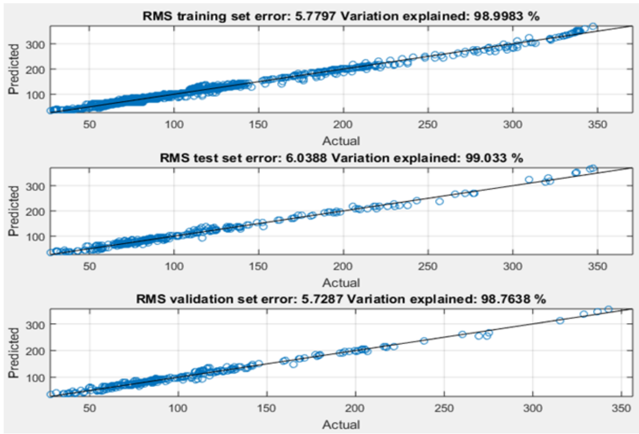



Fig 8: Multi-gene Regression, Model Prediction Scatter Plot

The input frequency for each input variable is shown in Fig 9,which measures the influence of input variables [15]. The graph demonstrates that $X_6$ which is $f_{yv}$ is the most influential factor and $X_3$ which is the stirrups confined core area aspect ratio is the less influential factor that affect the compression capacity in the proposed equation.

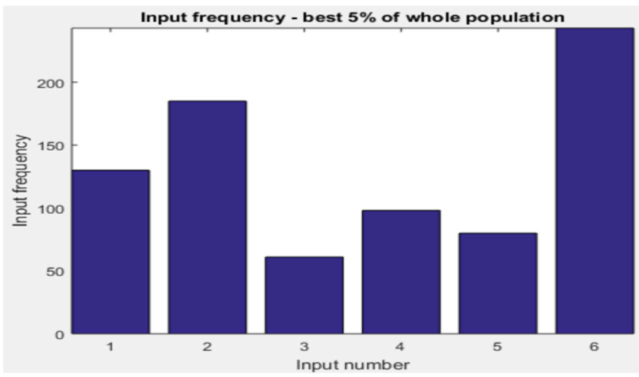
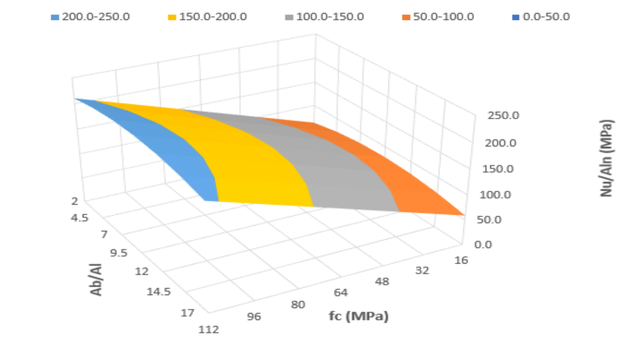



Fig 9: Population Input Frequency

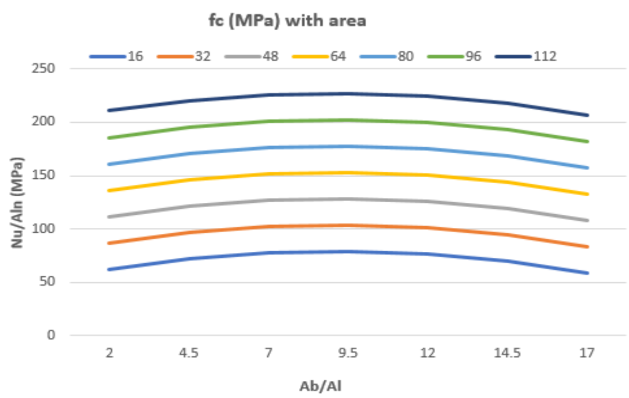
**Parametric Configurations**

In this section, the extracted equation is used to draw curves between two of the inputs with fixation of the other four inputs versus the output which is the local compression capacity of stirrups confined concrete.

Fig 10 illustrates the effect of peak compressive strength of concrete prisms with bearing area aspect ratio on the local compression capacity of stirrups confined concrete at the fixed values of stirrups confined core area aspect ratio equals 2.6, ratio of duct diameter to the section width equals 0.062, yield strength of stirrups equals 388, and volumetric ratios of confining stirrups equals 2.72. All these fixed values are the mean value for each parameter.



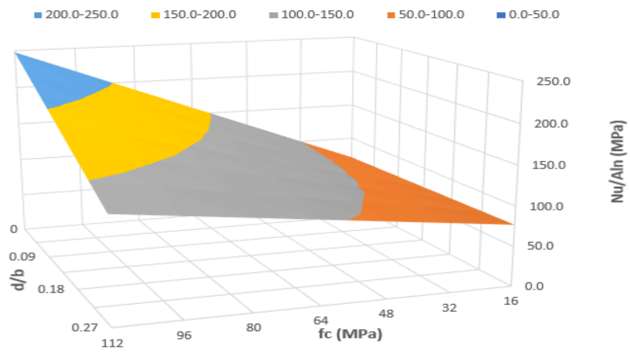

( a ) 3d curve




( b ) 2D curve

Fig 10: Effect of ($f_c$) and (Ab/Al) on LCCSCC at the Fixed Values of ($A_{cor}/A_l$ = 2.6), (d/b = 0.062), ($f_{yv}$ = 388), ($\rho_v$(%) = 2.72)

Fig 11 demonstrates the effect of peak compressive strength of concrete prisms with ratio of duct diameter to the section width on the local compression capacity of stirrups confined concrete. Other parameters were fixed as follows; bearing area aspect ratio (4.6), stirrups confined core area aspect ratio (2.6), yield strength of stirrups (388), and volumetric ratios of confining stirrups (2.72). All these fixed values are the mean value for each parameter. It is noted that for relatively high ratio of duct diameter to section width, the effect of concrete compressive strength is minimal. In general, increasing duct diameter decreases the local compressive strength. The reduction could reach 45% for $f_c$ =112 MPa and d/b = 0.27.

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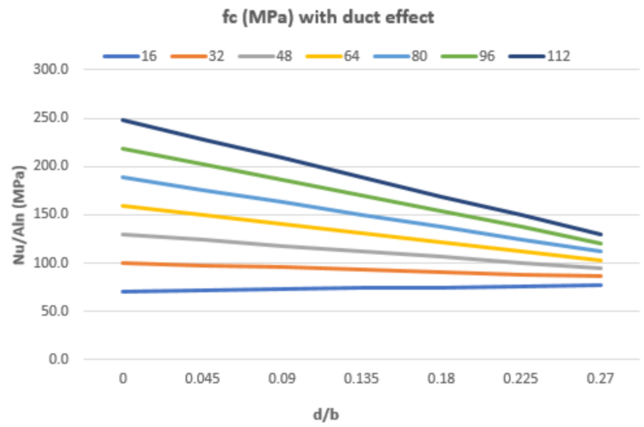


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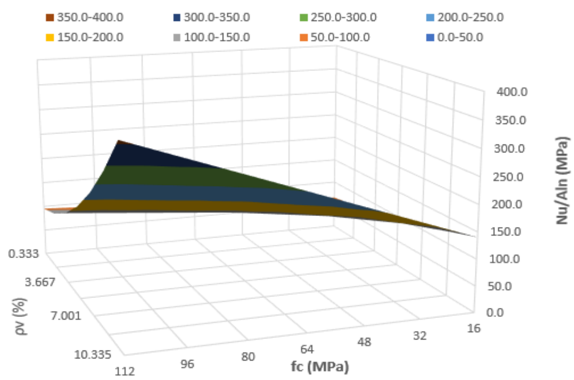
Fig 11: Effect of ($f_c$) and (d/b) on LCCSCC at the Fixed Values of ($A_b/A_l$ = 4.6), ($A_{cor}/A_l$ = 2.6), ($f_{yv}$ = 388), ($\rho_v$(%) = 2.72)

Fig 12 shows the effect of both peak compressive strength of concrete prisms and volumetric ratios of confining stirrups on the local compression capacity of stirrups confined concrete. It is noted that the effect of confining stirrups volumetric ratios on the compressive strength of concrete prism is more significant for higher grade of concrete strength.

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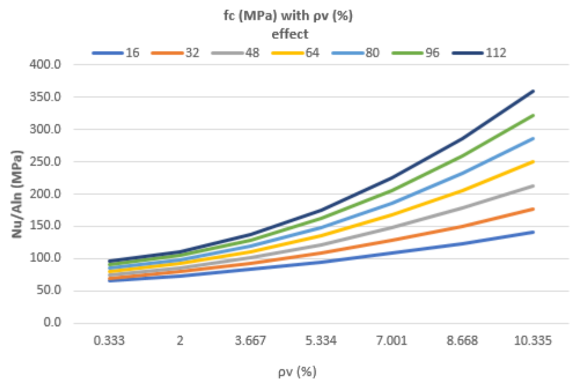
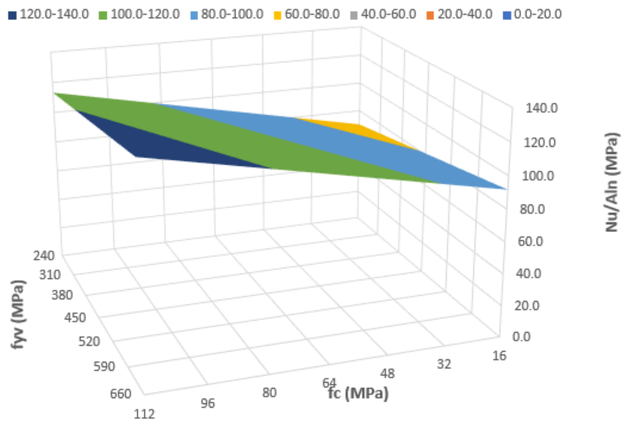



( b ) 2D curve

Fig 12 : Effect of ($f_c$) and ($\rho v(\%)$) on LCCSCC at the Fixed Values of ($A_b/A_l$ = 4.6), ($A_{cor}/A_l$ = 2.6), (d/b = 0.29), ($f_{yv}$ = 388)

Fig 13 demonstrates the effect of peak compressive strength of concrete prisms with the yield strength of stirrups on the local compression capacity of stirrups confined concrete. It is noted that the effect of stirrups yield strength is linear regardless of the peak compressive strength of concrete.

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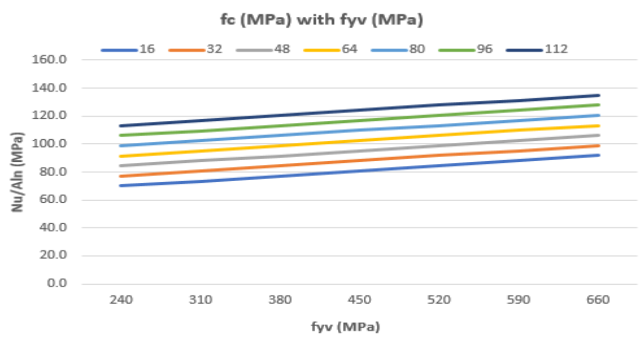
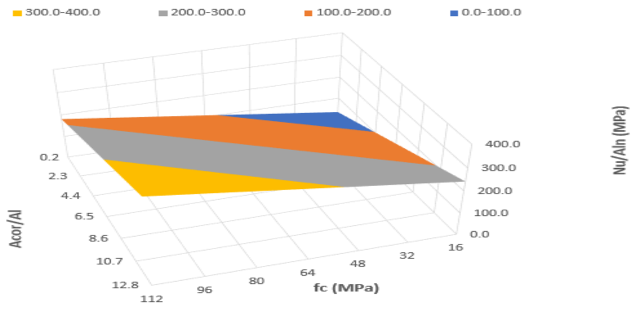



( b ) 2D curve

Fig 13 : Effect of ($f_c$) and ($f_{yv}$) on LCCSCC at the Fixed Values of ($A_b/A_l$ = 4.6), ($A_{cor}/A_l$ = 2.6), (d/b = 0.29), ($\rho_v(\%)$ = 2.72)

demonstrates the effect of peak compressive strength of concrete prisms with the stirrups confined core area aspect ratio on the local compression capacity of stirrups confined concrete. It is noted that the effect of core area aspect ratio is linear regardless of the peak compressive strength of concrete. The effect of core area is more significant compared to the effect of stirrups yield strength.

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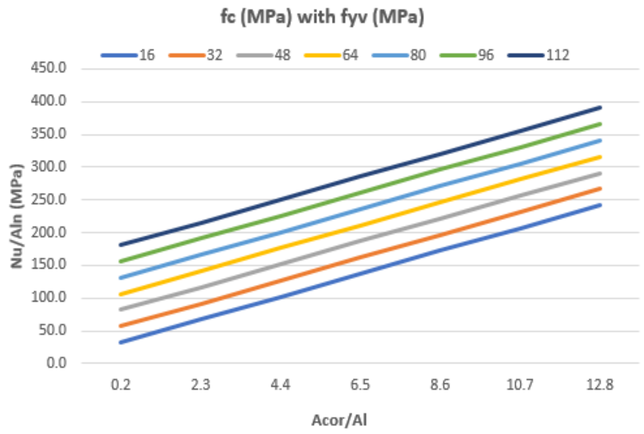


( b ) 2D curve

Fig 14 : Effect of ($f_c$) and ($A_{cor}/A_l$) on LCCSCC at the Fixed Values of ($A_b/A_l$ = 4.6), (d/b = 0.062), ($f_{yv}$ = 388), ($\rho_v(\%)$ = 2.72)

## Conclusions

Local compression concentration is an important issue in many engineering elements including post tensioned pre-stressed elements and bridge bearings. In this research, a new mathematical formula for estimating the bearing capacity of concrete in this critical area is developed. The Multi-Gene Genetic Programming (MGGP) model is created and a simple practical equation is formed to predict Local Compression Capacity of Stirrups Confined Concrete with a high degree of generalization and accuracy. The suggested model is developed using actual test results from the literature. The results obtained from model are compared to experimental results and an excellent agreement was reached. In conclusion, the MGGP approach is found to be highly effective and reliable in developing empirical equations based on real test results. The use of this approach is recommended for exploring other complicated issues where analytical methods cannot be reached.

The suggested formula is used to study the effect of many parameters on the LCCSCC. These parameters include; concrete compressive strength, duct diameter (if any), stirrups yield strength and volumetric ratio, local compressive area and core area aspect ratios.

From the parametric study carried out using the suggested formula, it is found that the peak compressive strength of concrete prisms decreases the effect of duct diameter. Increasing the volumetric ratios of confining stirrups can exponentially increase the local compression capacity of stirrups confined concrete. Both stirrups yield strength and core area aspect ratio linearly increase LCCSCC.

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