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RESEARCH PAPER

Investigation for Flood Flow quantification of Porous Asphalt with Different Surface and Subsurface Thickness

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Abstract

Permeable pavement can be considered one of the most successful alternatives solution to traditional asphalt, which industrially widely used due to their ability to allow rainwater or water from another source to leak through the earth surface to a tank below the surface; and that can be used for water-saving due lack of rains or to increase groundwater, as well as for irrigation. Another advantage that these permeable pavements may offer is their ability to remove contaminants that affect vehicle traffic, by moving across the pavement to the drainage system. The study aims to select the associations between the rainfall's intensity, the quantity of surface and subsurface runoff depending on the open-graded material and computational models to evaluate the porous pavements design. In this study, three aggregate distributions which are minimum, medium and maximum specifications are used. The results show that the medium gradation has met the requirements, and it is considered the best gradient, crumbed rubber are used. The optimal binder content satisfy the requirements is 6.3% for the porous asphalt mixtures. Nevertheless, when crumbed rubber is used with (10, 15 and 20)%. Crumb rubber percent used is 15% by the weight of Asphalt cement utilised for porous mix. The experimental results are utilised to produce mathematic models that estimated the surface and subsurface runoff for asphalt pavement. By the benefit of non-linear regression modelling using (SPSS) statistics software and making several equations to express those events to extend the software application, to sum up, cases that were not experimentally studied.

Keywords: Prediction; Porous asphalt; surface and subsurface thickness; flood flow

1. Introduction

The formulation of a porous asphalt mix necessitates choosing an acceptable aggregate grade and combining it with a desired binder content. The stability of its aggregate gradation depends on increasing the coarse aggregate matrix's stone-to-stone contact. The mineral filler and fine aggregates in the asphalt mortar, which also contains asphalt, hold the coarse aggregates together. As a result, the mineral filler, aggregates, and asphalt binder are crucial elements that should be taken into account. Rainfall in the natural world seeps into the earth, passes through it, and finally makes its way to streams, lakes, ponds, and subterranean aquifers. By contrast, the constructed environment seals the surface. Runoff from precipitation and snowmelt might cause floods. Without the natural filtering that nature intended, contaminants are swept from surfaces straight into rivers [1].

Tools for stormwater management may reduce how much the developed environment affects natural hydrology. However, they may sometimes result in bad decisions like removing whole stands of trees to make way for detention ponds. Porous asphalt surfaces enable the creation of more sustainable, sustainable, and smart land development designs. They recharge aquifers, decrease runoff, encourage infiltration that cleans stormwater, preserve streams, and save water. A typical porous pavement has a stone recharge bed under an open-graded top. The water permeates the stone bed and the permeable asphalt before gently seeping into the soil. Through filtration and microbiological activity, stormwater is cleaned of many toxins as it travels thru soils, porous asphalt, and stone recharge beds [2].

The engine train and the tyres are the two main contributors of traffic noise [3]–[6]. The cooling system, exhaust, and engine produce power train noise. It is unaffected by problems with pavement design, although it may be reduced by elements of the vehicle itself. However, tyre and pavement noise may be lessened by structuring the pavement surface to stop the creation or spread of noise. Noise from tyres on pavement may also be influenced by tyre design. The dynamics of the rolling process, the surroundings, the vehicle's speed, the kind of tyre, and the type of pavement surface all play a role in the complex interaction between the tyre and the pavement. By using porous road surfaces, certain European nations have effectively decreased tyre noise on highways [3], [7]–[9]. It is common practise to employ porous asphalt mixtures that include hard particles, a modified asphalt binder, and stabilising fibres. A porous asphalt surface has interconnected gaps in its structure that may let rainfall drain away when it's rainy outside. By obstructing various noise generating processes, the porous construction may help lessen tire/pavement noise. Additionally, porous pavements have shown durability, superior surface friction, and a reduction in splash and spray during downpours [10]. Porous asphalt differs from open graded friction courses (OGFCs), which were formerly utilised in many states in America. OGFCs often employed unaltered binders, at least in Indiana, had lower void percentages (10–15%), and were less durable than porous asphalt mixtures. In order to produce bigger air voids (18–22 percent), porous asphalt mixtures often include significantly gap-graded aggregate gradations [11]. To ensure strong aggregate interlock and long-lasting frictional qualities, high grade aggregates are required. The aggregate sizes that are now being utilised in Europe have altered from 14 mm to a range between 6 and 10 mm, producing greater air voids and less noise while retaining strong frictional qualities [12].

Friction is influenced by the pavement's surface texture that is a mix of gradation, aggregate quality, macrotexture and microtexture. The microtexture, which affects low speed frictional characteristics, is the tiny scale texture of the aggregates themselves. The macrotexture is the general pavement surface texture that facilitates water drainage and influences how quickly frictional characteristics drop as speed increases [13].

There are two primary categories for the crumb rubber technology utilised in asphalt pavement: dry process [14] and wet process [15]. The dry procedure involves combining crumb rubber with aggregate before adding asphalt to the prepared mixture, while the wet process involves adding crumb rubber to the base asphalt. Even though the dry process often results in unsteady road performance and poor mix design may cause pit, crack, and other illnesses. Nevertheless, compared to the wet approach, the dry method has more rubber powder, a greater rate of using waste tyres, superior high temperature stability, and a simpler building procedure, therefore it has received a lot of attention. Crumb rubber and asphalt are the perfect dampening materials for rubber asphalt pavement because they effectively reduce vibration and noise. Whenever a vehicle is moving over a road, the vibration will be communicated to the road's dampening material, generating internal displacement and friction and burning up a lot of vibration energy in the process. Conversely, the conventional pavement, which also stores some energy, deforms more than the rubber asphalt pavement. When the wheel moves away, the deformation returns, allowing the energy to be released [16].

A study by Welker et al., [17] shows that the water quality is almost similar in asphalt and concrete permeable pavements. This study indicates how much the permeable asphalt pavement is capable of reducing surface runoff quantity under different rainfall storms with a wide combination of roadways geometric design parameters. Scale concepts of typical urban surfaces, two green infrastructures (porous pavement and concave grassland), and two simulated rainfall intensities (low intensity=0.3 mm/min with a depth =25.4 mm, and high intensity=0.6 mm/min with a depth of 42.0 mm) have been built by Liu et al. [18], and their reactions to runoff as well as the effects of pervious surface positions and initial soil humidity on the runoff processes have been studied. Findings demonstrate that impermeable concrete surfaces generated runoff more quickly, with a 89 percent runoff coefficient. The grassland surface had the least runoff coefficient of 34 and 53percent and had a time to runoff that was approximately 25 times that of the impermeable surface. Concave grassland was able to successfully delayed the time until runoff compared to the impervious area, but porous pavement was able to drastically lower runoff discharge and peak flow rate. High rainfall intensity resulted in shorter runoff times, faster runoff discharge, and higher peak flow rates. In comparison to the previous surface under the top side, the prior surface under the lower side created runoff at a slower pace and with a smaller runoff coefficient. A strong negative association between the initial soil moisture and duration to runoff as well as a positive correlation between the runoff coefficient and initial soil moisture were discovered. These results contribute to a greater comprehension of how runoff from urban surfaces and green infrastructures works, which may aid with improved hydrology system planning for reducing urban floods.

Due to the big data generation and data mining, Machine learning (ML) techniques and Artificial Intelligence (AI) are the appropriate choice for developing novel approaches that can address emerging challenges [19]–[23]. The current study deals with the materials that used in the harsh conditions and hot climate for producing porous asphalt. Experimental tests were conducted on several mixtures applied in different methods to identify the best mixture for the harsh conditions and hot weather [24]. After finding the successful mixture, it is laid on a roadway with the drainage system under hydraulic properties and different geometrical conditions of the road [25]. However, the current study aim to predict surface and subsurface flow for different porous asphalt thicknesses based on the dada collected in [25], the data gained from the laboratory work is 60 attempts for three thicknesses (25, 37.5 and 50 mm), five slopes as (0.0, 2.5, 5, 7.5 and 10%) and four rainfall intensities as (20, 40, 60 and 80L/min). Non-Linear Modelling Regression were performed by utilizing SPSS Statistical Software was utilised to predict the correlation between the observed and estimated runoff from surface and subsurface layer.

2. Methodology

This study includes the relationship between the surface and subsurface runoff for permeable asphalt pavement. The experimental data of rainfall simulation system utilised to demonstrate the statistical model by using non-linear regression (SPSS) approach.

2.1 Non-Linear Regression modelling

SPSS software is utilised for quantitative analysis and is utilised as a full statistical package depending on an interface point and click. From the data of creation in1960 by Norman in cooperation with other programmers [26], this computer-programming has been commonly version 20 utilised by scientists to conduct quantitative analysis.

It's not as simple as it seems to tell a regression model to be linear or nonlinear. Users could assume that nonlinear formulas describe curvature whereas linear equations generate straight lines. That is unfortunately untrue. Since both kinds of models may match curves to the data, it is not what distinguishes them from one another.

A model of linear regression has a very specific shape. A prediction model is said to be linear in statistics if all of its components are constant and independent variables (IVs).

Dependent variable = constant + parameter * IV + ... + parameter * IV

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k \tag{1}$$

A mathematical approach called nonlinear regression uses a produced line to fit a formulas to certain data. Nonlinear regression, which is nonlinear in the variable, illustrates correlation that used a curve, similar to a linear regression that employs a straight-line formula (including $Y = c + mx$).

Here is how a basic nonlinear regression expression is written:

$$Y = f(X, \beta) + \epsilon \tag{2}$$

Whereas: X refers to P predicting vector β refers to k variable vector F (-) refers to the constant regression function ϵ is the error term

Also the model can be placed alternatively as following:

$$Y_i = h\left[x_i(l), x_i(2), \ldots, x_t^{(m)}; \theta_l, \theta_2, \ldots, \theta_n\right] + E_i \tag{3}$$

Whereas: Yi refers to the responsive parameter h refers to the function x refers to the input θ refers to the expected variable

A rainfall simulation system is designed with dimension of (1.5x1.0)m to develop the associations between the runoff volume of subsurface and surface from a permeable asphalt pavement as shown in figure 1. To get a general understanding of the hydraulic flow conditions and the runoff performance that occurred within, two layers permeable and conventional pavement. The thickness of the porous layer is (2.5, 3.75 and 5) cm, and the traditional layer is 8cm. The samples are prepared with the modifiers utilised the best ratio of crumb rubber, the previous test indicated that the use of crumbed rubber at various rate advances the characteristics of porous asphalt mixture. Crumb rubber percent used is 15% by the weight of Asphalt cement utilised for porous mix, five slopes as (0.0, 2.5, 5.0, 7.5 and 10.0) % in short direction, and four discharge as (20, 40, 60 and 80) L/min are tested. The result demonstrated that 5cm thickness is suitable for permeable asphalt pavement under high side slopes, whereas it increases subsurface runoff and decreases surface runoff water (Fig 2).

The best way to understand the procedure used for designing the predictive model, is through the flowchart shown in Figure 3.

2.2 The Criteria of Efficiency

Presentation and evaluation of the effectiveness criteria utilised in this research. These are six criteria: effectiveness of Nash-Sutcliffe, root mean square error, mean absolute error, variance, agreement index and coefficient of determination to provide enough data on the errors of systematic in the simulation modelling as illustrated below.

2.2.1 Nash-Sutcliffe Efficiency Coefficient (NSEC)

Nash and Sutcliffe's [27] suggested efficiency is described as one minus the sum of the absolute square variation between the values of observed and predicted normalized by the difference of observed magnitudes during the period under study. It has been determined as:

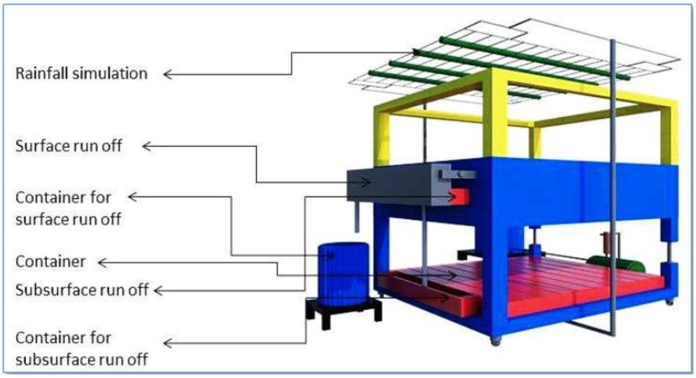

Figure 1: *Details of apparatus of rainfall simulation phenomena [25]..*

Figure 2: *The collected runoff water under pavement layers A) Rainfall simulator system; B and C) Surface and Subsurface runoff.*

$$NSEC = 1 - \left(\frac{\sum_{i=1}^{n} (y_b - y_p)^2}{\sum_{i=1}^{n} (y_b - \overline{y_b})^2} \right) \tag{4}$$

Where: y_b: observed value. y_p: predicted value. y_b: mean value of yb n: number of data.

NSEC's range ranges from (1.0) perfect fit to $-\infty$. Effectiveness below zero shows that a good analyst comparison with the modelling would have been the magnitude average of the pragmatic time sequence. Nash-Sutcliffe's biggest disadvantage is the fact that the variances between the values of predicted and observed are measured as squared values. Due to higher values are highly over-estimated in a time series, while lower values are ignored [28].

2.2.2 Agreement Index (d)

Willmot [29] suggested that the agreement index d and r overawed the inattentiveness of (NSEC) and to alterations the means and variances observed [28]. The index's agreement is defined as an error of a mean-square proportion and the probable errors [29], [30]:

$$d = 1 - \frac{\sum_{i=1}^{n}(y_b - y_p)^2}{\sum_{i=1}^{n}\left(|y_p - \overline{y_b}| + |\,y_b - \overline{y_b})^2\right.} \quad (5)$$

The (d) is ranges from (0 to 1) which means no correlation and perfect fit, respectively.

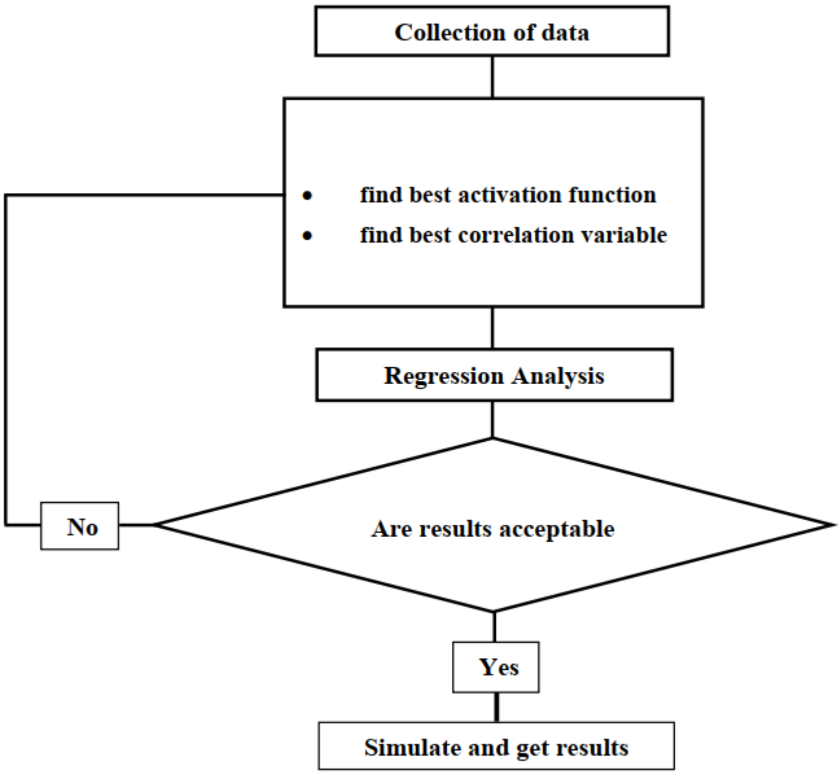

Figure 3: *The collected runoff water under pavement layers A) Rainfall simulator system; B and C) Surface and Subsurface runoff.*

2.2.3 Determination Coefficient (r)

During this investigation, the determination coefficient, r, was written by:

$$r = 1 - \frac{\sum_{i=1}^{n}(y_b - y_p)^2}{\sum_{i=1}^{n}(y_b - \overline{y_b})^2} \quad (6)$$

2.2.4 Mean Absolute Error (MAE)

The mean absolute error MAE was represented by:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_b - y_p| \quad (7)$$

The above variables were utilised to evaluate the performance of the developed SPSS model. If MAE is equal to zero, the model is treated as excellent [31].

2.2.5 Variance (V)

The difference was permeable by:

$$VAF = \left[1 - \frac{\operatorname{var}\left(y_b - y_p\right)}{\operatorname{var} y_b}\right] \times 100 \tag{8}$$

Whereas var denotes the variance. If VAF is (100) %, the model is treated as excellent [32].

2.2.6 Root Mean Square Error (RMSE)

The mean root square error was written by eq. (6):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(y_b - y_p\right)^2}{n}} \tag{9}$$

Where RMSE is 0, the model is treated as excellent [33]

3. Results and Discussion

The data gained from the laboratory work is 60 attempts for three thicknesses (25, 37.5 and 50 mm), five slopes as (0.0, 2.5, 5, 7.5 and 10%) and four rainfall intensities as (20, 40, 60 and 80L/min). Non-Linear Modelling Regression were performed by utilizing SPSS Statistical Software was utilised to predict the correlation between the observed and estimated runoff from surface and subsurface layer.

3.1 Surface Flow (25 mm thickness)

Figure 4 demonstrate the correlation between predicted and observed surface-flow at (25) mm thickness for the layer of open-graded friction course, by several attempts utilizing mathematical equations to achieve the best model expression for the regression coefficient (R^2) value and many efficiency criteria. The second attempt gave the highest (R^2) value, in addition to the statistical coefficients residue within limits.

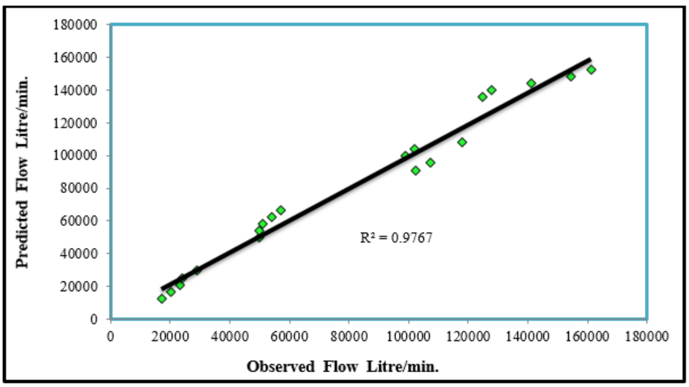

Figure 4: *The correlation between predicted and observed surface-flow at 25 mm thickness.*

3.2 Sub-Surface Flow (25 mm thickness)

Figure 5 demonstrate the relationship between predicted and observed flow at (25) mm thickness for permeable asphalt-pavement. The highest (R^2) value and the best coefficient value is predicted from the second attempt.

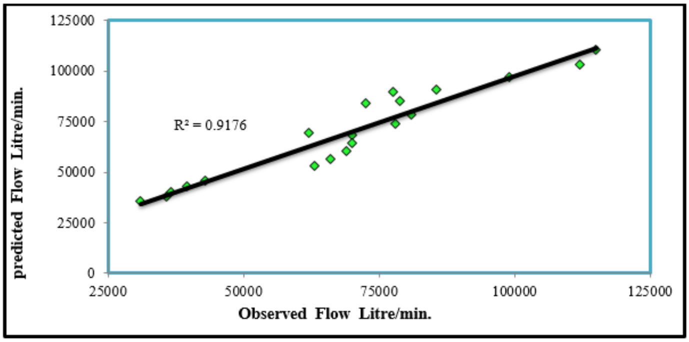

Figure 5: *The correlation between predicted and observed subsurface-flow at 25 mm thickness.*

3.3 Surface Flow (37.5 mm thickness)

Figure 6 demonstrate the relationship between predicted and observed surface-flow at (37.5) mm thickness for permeable asphalt-pavement. The highest (R^2) value and the best coefficient value is predicted from the third attempt.

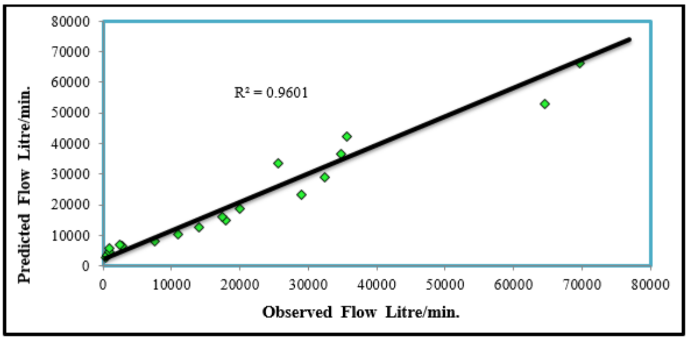

Figure 6: *The correlation between predicted and observed surface-flow at 37.5 mm thickness.*

3.4 Sub-Surface Flow (37.5 mm thickness)

Figure 7 demonstrate the relationship between predicted and observed subsurface-flow at (37.5) mm thickness for permeable pavement. The highest (R^2) value and the best coefficient value is predicted from the third attempt.

3.5 Surface Flow (50 mm thickness)

The best regression coefficient (R^2) value and the remain statistical coefficient is achieved from the third attempt, the correlation between predicted and observed surface-flow at (50) mm thickness for OGFC as demonstrated in figure 8.

3.6 Sub-Surface Flow (50 mm thickness)

The highest regression coefficient value and the best residue statistical coefficient value are gotten from the first attempt for the last thickness of permeable pavement. Figure 9: demonstrate the correlation between predicted and observed subsurfaceflow at 50 mm thickness. In harmoney, same results presented in Table 1.

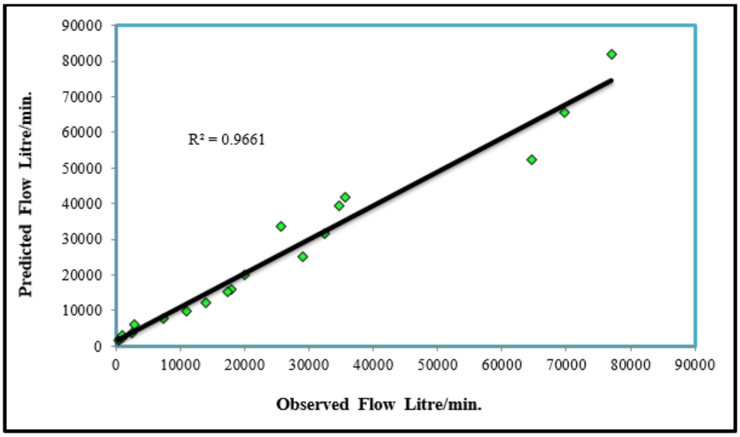

Figure 7: *The correlation between predicted and observed subsurface-flow at 37.5 mm thickness.*

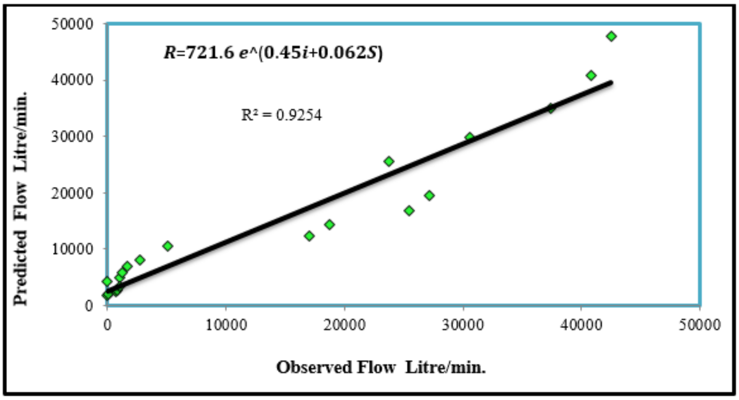

Figure 8: *The correlation between predicted and observed surface-flow at 50 mm thickness.*

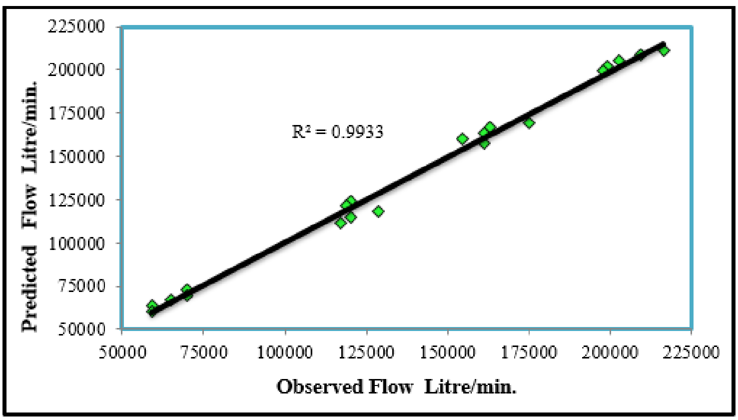

Figure 9: *The correlation between predicted and observed subsurface-flow at 50 mm thickness.*

Table 1: *The summary of the obtainable results.*

Case ID	NSEC	MAE	RMSE	VAF	d	R2	r
Surface-flow at 25 mm thickness	0.92	0.21	0.23	92.5%	0.85	0.977	0.98
Subsurface-flow at 25 mm thickness	0.78	0.4	0.37	82%	0.81	0.925	0.95
Surface-flow at 37.5 mm thickness	0.92	0.11	0.17	91%	0.94	0.97	0.99
Subsurface-flow at 37.5 mm thickness	0.953	0.11	0.18	94.4%	0.93	0.966	0.98
Surface-flow at 50 mm thickness.	0.83	0.24	0.30	90%	0.88	0.94	0.98
Surface-flow at 50 mm thickness.	0.90	0.25	0.20	93%	0.88	0.98	0.99

4. Conclusions

Understanding the drainage behavior of OGFCs roads came from developing the simulation model and using it on non-linear sections, converging sections, and the field monitoring site for surface and subsurface drainage. The following conclusions are drawn from this work:

• For the first time, runoff hydrograph forecasts for OGFC's roads are provided. These hydrographs demonstrate that the initial discharge from the road is delayed by OGFCs in comparison to ordinary pavements, and that the steady state flow in an OGFCs layer takes a long time to attain.

• The prediction of different surface and subsurface layer thickness show that the thickness 37.5 mm give best Nash-Sutcliffe Efficiency Coefficient for both surface and subsurface, which about 0.92 and 0.953, respectively.

• Nash-Sutcliffe Efficiency Coefficient was decreased with decreasing the surface thickness to 25 mm, while NSEC increased with decreased the subsurface thickness to 50 mm.

Conflicts of Interest: **The authors declare no conflict of interest to any party.**

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