Study on Building Runway Water Depth Model Based on the Placement of Water Level Gauge

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***Abstract*—This study presents the analysis of runway water depth predictions based on different placement of water depth gauges. Fuzzy logic method is used to set up the numerical runway water depth models for prediction. The influenced parameters of models include runway average macrotexture depth, drainage length, rainfall intensity and cross slope. The results showed acceptable runway water depth predictions can be obtained through the placement of either normal numbers of water depth gauges or fewer gauges in the experiment.**

***Index Terms*—frunway water depth; fuzzy logic modeling; water level gauge**

I. INTRODUCTION

According to the 2016 ICAO Safety Report [1], runway safety related accidents include runway excursion/incursion, undershoot/overshoot, tail-strike and hard landing which accounted for the majority (53%) of all global accidents during 2015. From 2007 to 2016, there were totally 43 civil transportation category aircraft occurrences in Taiwan [2]. Of those 43 occurrences, runway excursions overall were the most frequent and a total of 12 occurrences were reported. All these 12 occurrences occurred during the landing phase of flight. The most common causes/factors to these runway excursion occurrences were flight crew and weather related factors. ICAO Annex 14 [3] recommends when water is on a runway, a description of the runway surface conditions should be made available using the following terms: DAMP, WET and STANDING WATER. The definition of STANDING WATER is that: a runway where more than 25 per cent of the runway surface area within the required length and width being used is covered by water more 3 mm deep which is difficult to assess even by an experienced observer. In ICAO Annex 6, this runway condition is called as a contaminated runway. If runway water accumulates to a high enough depth such as 3mm, dynamic hydroplaning may be occurred when tire travelling through this water during aircraft landing. Once dynamic hydroplaning occurs, the water pressure in front of tire(s) may equal to the weight of landing aircraft and separates tire(s) from the runway resulting in a loss of contact with the runway. With one or more tires loss contact with the runway, directional control of aircraft becomes more difficult and runway excursion may occur with the combination of poor pilot handling or control. In October 2016, the U.S. Federal Aviation Administration required that airport operators should declare runway condition code of the Runway Condition Assessment Matrix (RCAM) to pilots [4]. Runway water depth is one of these parameters in the RCAM However, to declare runway condition to pilots need expensive labor costs and runway water depth cannot be fully assessed by airport operators. On the other hand, safety concerns and high maintenance and construction costs incurred if real-time measuring instruments were used. Furthermore, the requirement t to assess whether the accumulated runway water impact aircraft operation or not, water depths on runway is a key factor to accident investigation and needed to be clarified as soon as possible.

The development of water depth predictor has developed since 1971. To predict the water depth on various ungrooved pavements, Gallaway [5] developed an equation based on the tests at the Texas Transportation Institute (hereinafter TTI equation). The TTI equation was determined by regression method to fit the experimental test data. The TTI equation was widely used or recommended in the field of highway or runway water depth prediction. From the test data as listed in [5], if the datum plane was at top of texture, the multiple correlation coefficients (R2) of the predicted water depths by using the regression equations were unsatisfactory. In 1984, Wambold et al. [6], developed a computer program in Pennsylvania Transportation Institute to predict water depth analytically. However, it predicts significantly lower water depths than did the TTI equation which was identified in reference [3].

Although this TTI equation could estimate the pavement water depth, there were some disadvantages, such as, shallow runway macro texture depths, large time scale of rainfall rate (per hour), and large deviation between the experimental data and the derived regression models. The authors therefore would like to provide a new model with the incorporation of different rainfall rates

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from 7mm to 14mm in a 6-minute rainfall period, deeper runway macro texture depths ranging from 0.4 to 1.2 mm, and different cross slopes in the experiment.

Instead of using regression method to estimate runway water depths, an alternate approach to predict runway water depth was developed through Fuzzy Logic Modeling (FLM) technique. In earlier development of the fuzzy logic algorithm, Zadeh used the fuzzy sets to simulate physical parameters with membership functions. In 1985, Takagi and Sugeno [7] used internal functions, instead of the fuzzy sets, in developing the fuzzy logic algorithm. Tan and Xie [8] applied the same theory to simulate microelectronic processes with very good accuracy in 1995. Since year 1998, the technique of FLM has been applied to other applications, such as: nonlinear unsteady aerodynamics modeling [9]-[11], diagnostic of engine integrity [12], aircraft structural health monitoring [13], by Lan and Chang et al. A preliminary study on the prediction of runway water depths verified accurate results could be obtained through FLM modeling method [14]. The successfully application of FLM method to different areas demonstrated the technique has an excellent data correlation capability and predictive accuracy in modeling systems with nonlinear, unsteady and complex characteristics.

A real time observation and report of 3 mm runway water depth is practically impossible at current stage. Information gaps of aircraft operations on wet runway exist between the user (flight crew) and the provider (aerodrome) needs to be filled. The main objective of this study is using Gallaway's test data, either reduced or un-reduced, to present the model development through FLM technique and to demonstrate the capability of resulting models to predict accurate runway water depths in real time. The experimental plans will use 3 to 6 sets of water level gauge to measure instantaneous water depth. To find the best gauge location in the experiment, a preliminary study is arranged and FLM method is used to set up the numerical models in this paper.

II. Theoretical Development

To set up the relations between input variables and the accumulated water depth of the runway model, FLM technique is adopted in the present study. Modeling process start from dividing the input variables data into many groups, functional relations are set up between each input and output data group. Membership functions are used to quantify the number of relationship between input and output variables. Two main tasks, one is the identification of the coefficients of the internal functions which is called parameter identification, the other one is structure identification to identify the optimal structure of fuzzy cells of the model, are involved in the FLM process. Details of the FLM technique are described in the follows.

The fuzzy logic model uses many internal functions to cover the tested data ranges of the input variables as follows:

$$P^i = y_i(x_1, x_2, \cdots, x_r, \cdots x_k) = p_0^i + p_1^i x_1 + \cdots + p_r^i x_r + \cdots p_k^i x_k \quad (1)$$

where p_r^i, r=0, 1, 2,…, k, are the coefficients of internal functions y_i, and k is number of input variables, y_i is denoted as an estimated output, and x_r are the variables of the input data.

The values of each input variable are divided into several ranges, each of which represents a membership function with $A(x_r)$ as its membership grade. One membership function from each variable constitutes a fuzzy cell. For i^{th} cell, the corresponding membership grades are represented by $A_r^i(x_r)$, r=0, 1, 2,…, k. The membership functions allow the membership grades of the internal functions for a given set of input variables to be calculated. The membership functions partition the input space into many fuzzy subspaces, which are called the fuzzy cells. The total number of fuzzy cells is $n = N_1 \times N_2 \times \cdots \times N_r \times \cdots \times N_k$. For a variable x_r, the number of membership function is N_r. In this study, the overlapped triangular membership function is used to represent the grades of internal functions.

A fuzzy cell is formed by taking one membership function from each variable. The total number of cells is the number of possible combinations by taking one membership function from each input variable. For every cell, it has a fuzzy rule to guide the input and output relations. The rule of the i^{th} cell is stated as:

if x_1 is $A_1^i(x_1)$, and if x_2 is $A_2^i(x_2)$, and ... and if x_k is $A_k^i(x_k)$, then the cell output is

$$P^i(x_1, x_2, \cdots, x_r, \cdots x_k) = p_0^i + p_1^i x_1 + \cdots + p_r^i x_r + \cdots p_k^i x_k \quad (2)$$

where $i = 1, 2, \ldots, n$ the index of the cells, n is the total number of cells of the model; $P^i(x_1, x_2, \cdots, x_r, \cdots x_k)$ is the internal function with parameters $p_0^i, p_1^i, \ldots, p_r^i, \ldots, p_k^i$ to be determined, and $A_k^i(x_k)$ denotes the membership function for x_k. Each function covers a certain range of input variables.

In each fuzzy cell, the contribution to the cell output is based on the internal function, equation (2). The final prediction of the outcome is the weighted average of all cell outputs after the process of fuzzy rule inference. The output estimated by the fuzzy logic algorithm corresponding to the j^{th} input ($x_{1,j}, x_{2,j}, \ldots, x_{r,j}, \ldots x_{k,j}$) is as follows:

$$\hat{y}_j = \frac{\sum_{i=1}^{n} product\left[A^i(x_{1,j}), \cdots, A^i(x_{r,j}), \cdots, A^i(x_{k,j})\right] p^i}{\sum_{i=1}^{n} product\left[A^i(x_{1,j}), \cdots, A^i(x_{r,j}), \cdots, A^i(x_{k,j})\right]} \quad (3)$$

In equation (3), $product[A^i(x_{1,j}), \ldots, A^i(x_{r,j}), \ldots, A^i(x_{k,j})]$ is the weighted value of the i^{th} cell; and the index j of the data set, where j=1,2,…, m, and m is the total number of the test data; and the "*product*" stands for product operator of its elements in this study.

To identify the coefficients of the internal functions, the unknown coefficients are adjusted with the gradient-descent method by minimizing the sum of squared errors (SSEs) and the structure of fuzzy cells is optimized by maximizing the squared multiple correlation coefficients (R^2) using equations (4) and (5) respectively.

$$SSE = \sum_{j=1}^{m} (\hat{y}_j - y_j)^2 \tag{4}$$

$$R^2 = 1 - \frac{\{\sum_{j=1}^{m} (\hat{y}_j - y_j)^2\}}{\{\sum_{j=1}^{m} (\bar{y} - y_j)^2\}} \tag{5}$$

where $\hat{y}_j$ is the output of the fuzzy logic model at point *j*, y_j is the test data used for the model training at point *j*; $\bar{y}$ is the average value of all test data, and *m* is the total number of test data. The model training is to determine the unknown coefficients of the internal functions, p_r^i, by maximizing the value of R^2. These coefficients are determined by an iterative equation (6) to minimize the SSEs.

$$p_{r,t+1}^i = p_{r,t}^i - \alpha_r \frac{\partial(SSE)}{\partial p_r^i} \tag{6}$$

where α_r is the step size in the gradient method, subscript index *t* denotes the iteration sequence. The iteration during the search sequence stops when one of the specified criteria, the cost function, relative error or maximum iteration numbers, is met.

In the fuzzy logic model, the structure of fuzzy cells is indicated by the number of membership functions. The model structure identification is tied up with parameter identification. For a fuzzy logic model with multiple variables, the structure is the combination of the numbers and forms of the membership functions assigned to all input variables. Since the sequence defines the one-to-one relationship between the numbers and the forms for each variable, the structure can be uniquely described by the numbers. The optimal structure of fuzzy cells is identified by maximizing the R^2 (equation 5). The best model structure searching flow is shown graphically in Fig. 1. Fig. 2 shows the flowchart of parameter identification processes.

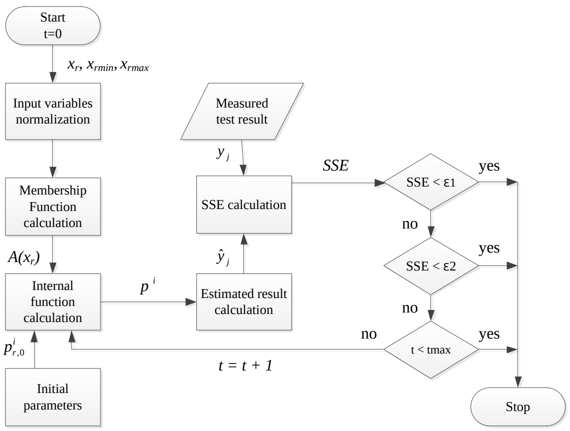

Figure 1. Flowchart of parameter identification process

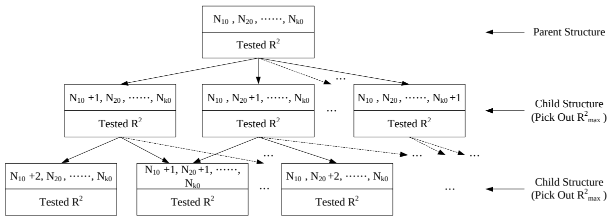

Figure 2. Best model structure searching flow

III. Rnuway Water Depth Modeling

A. Data for Modeling

Gallaway's test data as listed in table 10, surface No. 1 of reference 6, is used for the present study. Variables influence the measured water depths including average macrotexture depth, drainage length, rainfall intensity and cross slope. In the original data, test ranges of each variable were chosen to meet the characteristics of Texas highway pavements. Since the cross slope of typical runway usually covers the range from 0.4% to 1.5%, measured water depths which tested at 4% cross slope of Gallaway's data were not adopted in setting up the fuzzy logic model. Therefore, only 80 records of data were used to set up the numerical model through FLM method.

B. Fuzzy Logic Models

According to reference 6, water depths were measured at regularly spaced drainage lengths for various combinations of rainfall intensity and pavement cross slope. Locations of water depth measurement were at approximately six feet intervals, which were 6.0, 13.0, 18.5 and 24.0 feet of drainage length. From previous research (reference 15), the established models showed a 99.75% accuracies in the prediction of runway water depths by using the whole records of data in the training of fuzzy logic model. The model predictive accuracy is unknown if test data used for model training were measured at non-equidistant intervals. For this purpose, the present study first uses these 80 records of data to set up the fuzzy logic model (hereinafter model I). Then, water depths measured at 18.5 or at 13.0 feet of drainage length are removed from the data set. The same FLM method is applied again to set up fuzzy logic models using these two reduced data sets, one containing only data measured at 6.0 feet, 13.0 feet and 24.0 feet of drainage length (hereinafter model II) , and the other one containing only data measured at 6.0 feet, 18.5 feet and 24.0 feet of drainage length (hereinafter model III). Water depths at 18.5 feet and 13.0 feet of drainage length are estimated by using the established model II and III respectively. The results are then compared with the results obtained from model I. This procedure is applied in the present study to test the placement of water level gauge flexibility and predictive accuracy of its established fuzzy logic models.

The runway water depth model is assumed to depend on four variables: average macrotexture depth, drainage length, rainfall intensity and cross slope. A functional relation is established between runway water depth and its influencing variables for modeling as shown in equation (7).

$$d = f(S, I, T, L) \quad (7)$$

where d represents water depth, S is the cross slope, I the rainfall intensity, T the average macrotexture depth, and L the drainage path length. The template is used to format your paper and style the text. All margins, column widths, line spaces, and text fonts are prescribed; please do not alter them. You may note peculiarities. For example, the head margin in this template measures proportionately more than is customary. This measurement and others are deliberate, using specifications that anticipate your paper as one part of the entire proceedings, and not as an independent document. Please do not revise any of the current designations.

IV. Numerical Results and Discussions

Through the fuzzy logic modeling processes, the final runway water depth models are established by using the above mentioned un-reduced (4 water level gauges) and reduced (3 water level gauges) data sets in the model trainings. In Table I, the numbers below each input variables represent the number of membership functions. The total number of fuzzy rules (n) in each model is the product of each numbers which presented in column 6. The last column shows the final squared multiple correlation coefficients (R^2).

TABLE I. Fuzzy Rule Numbers and Squared Correlation Coefficients of FLM Models

	S	*I*	*T*	*L*	*n*	R^2
Model I	2	3	5	4	120	0.9989
Model II	7	3	5	4	420	0.9999
Model III	3	3	6	4	216	0.9998

The R^2 values of model I, II and III are all close to 1, which means the predictions of runway water depths are nearly exactly the same as the actual empirical values of data. This indicates that the measured water depths can be accurately estimated by all the established models.

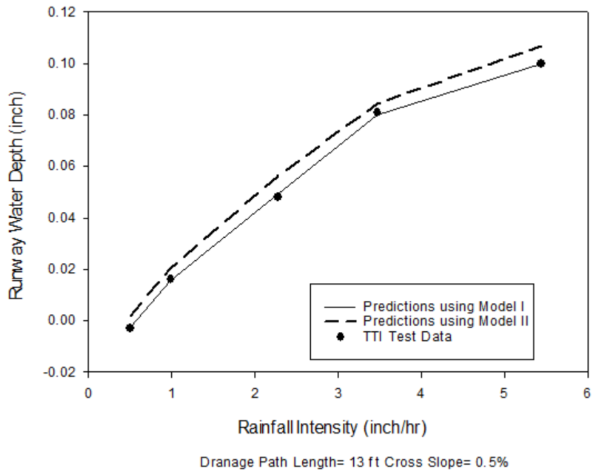

Figure 3. Comparison of water depths predicted by model I and II at fixed drainage length L = 13.0 feet for cross slope=0.5%

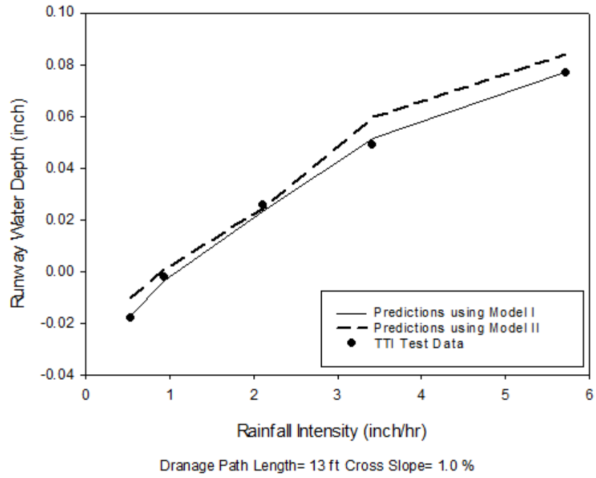

Figure 4. Comparison of water depths predicted by model I and II at fixed drainage length L = 13.0 feet for cross slope=1.0%

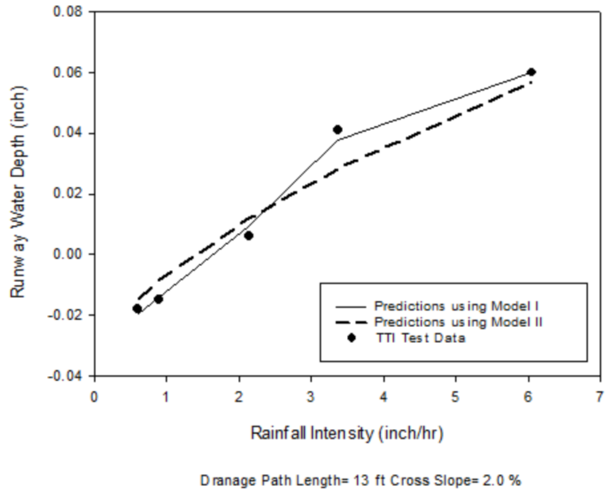

Figure 5. Comparison of water depths predicted by model I and II at fixed drainage length L = 13.0 feet for cross slope=2.0%

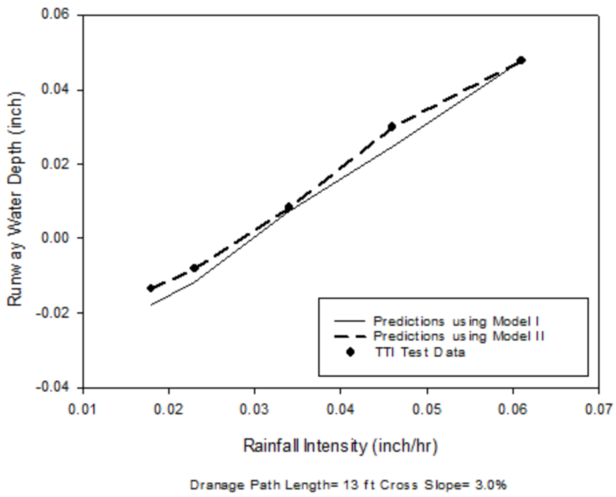

Figure 6. Comparison of water depths predicted by model I and II at fixed drainage length L = 13.0 feet for cross slope=3.0%

The established models II and III are used to predict water depths at 18.5 feet and 13.0 feet of drainage length to test the use of fewer gauges and the placement of water level gauge at non-equidistant intervals and the use of fewer gauges. Fig. 3-6 show the comparisons between the measured water depths and the water depths predicted by model I and II at fixed drainage path length L = 13.0 feet for varying rainfall intensity, cross slope, and average macrotexture depth. The comparisons of model I and III at fixed drainage path length L = 18.5 feet are shown in Fig. 7-10.

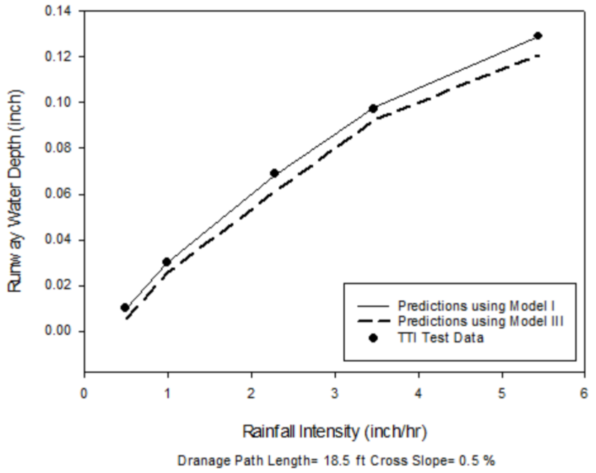

Figure 7. Comparison of water depths predicted by model I and III at fixed drainage length L = 18.5 feet for cross slope=0.5%

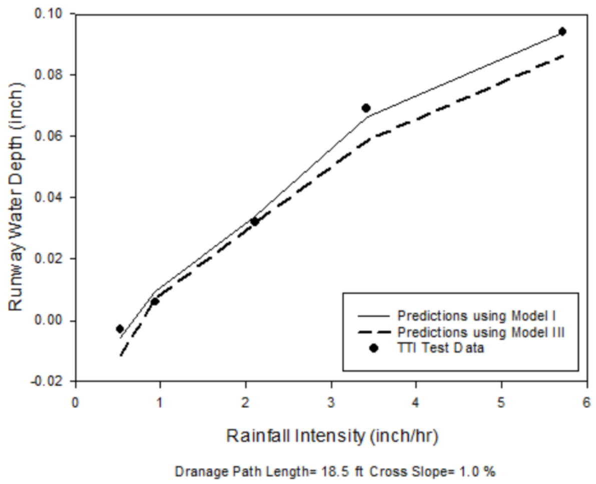

Figure 8. Comparison of water depths predicted by model I and III at fixed drainage length L = 18.5 feet for cross slope=1.0%

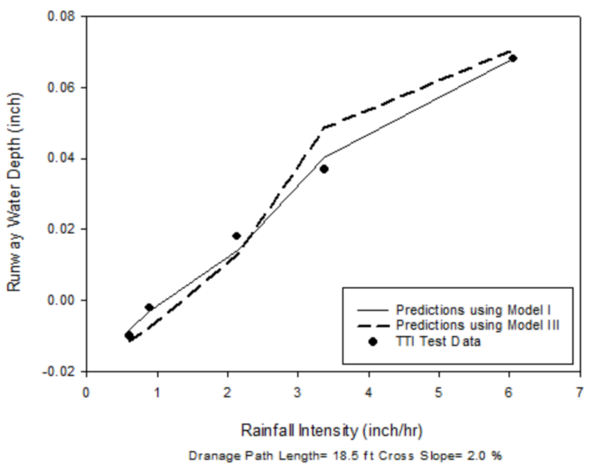

Figure 9. Comparison of water depths predicted by model I and III at fixed drainage length L = 18.5 feet for cross slope=2.0%

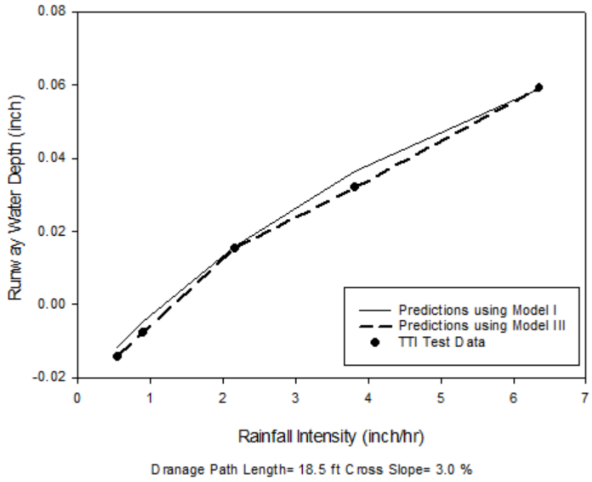

Figure 10. Comparison of water depths predicted by model I and III at fixed drainage length L = 18.5 feet for cross slope=3.0%

The predicted sums of squared errors (SSE) from model III and model II are compared with those results from model I as shown in Table II.

TABLE II. FUZZY RULE NUMBERS AND SQUARED CORRELATION COEFFICIENTS OF FLM MODELS

	At 13.0 feet of drainage length		**At 18.5 feet of drainage length**	
model	**model I**	**model II**	**model I**	**model III**
SSE	4.68×10^{-5}	7.53×10^{-4}	6.65×10^{-5}	6.92×10^{-4}

In Table II, the SSE's of model I show deviations of prediction from actual empirical values of data at 13.0 and 18.5 feet of drainage length which are all smaller by a scale of 10^{-1} than those deviations of prediction of either model III or model II. Instead of using water depth measurement data at 3 locations, model I used data which measured at 4 locations in setting up the model. This indicates that a tight fitting of the model to the data can be obtained if more water level gauges are used in collecting the test data. Although Model II and Model III used fewer gauges and measurement data in setting up the models, their predictions showed satisfactory results could be obtained. The established FLM models can be used by aerodrome and airport control tower personnel to monitor and broadcasting runway status to assist flight crew's takeoff and landing decision making.

V. CONCLUDING REMARKS

The objective of this study was to present an alternate analytical method to predict water depths on the runway and to illustrate its predictive accuracy. This method was based on Gallaway's test data to establish the water depth model through FLM technique. The numerical results showed that the established model could predict relatively accurate water depths. In real time application, the established model can assist aerodrome and airport control tower personnel to monitor and broadcasting runway water depth condition with respect to potential hydroplaning risk. To improve the accuracy of real time broadcasting capability, a smaller scale of rainfall intensity, such as rainfall rate per 6 minutes, can be adopted in the future to develop runway water depth prediction models.

Coflict of Interest

The authors declare no conflict of interest.

Author Contribution

Peida Lin conducted the research, experiment and wrote the paper; Yannian Lee analyzed the data; Both authors had approved the final version.

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