Storage Capacity Modeling of Reservoir Systems Employing Performance Measures

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Abstract—Developing a prediction relationship for total (i.e. within-year plus over-year) storage capacity of reservoir systems is beneficial because it can be used as an alternative to the analysis of reservoirs during designing stage and gives an opportunity to planner to examine and compare different cases in a fraction of time required for complete analysis where detailed analysis is not necessary. Existing relationships for storage capacity are mostly capable of estimating over-year storage capacity and total storage capacity can be obtained through relationships for adjusting over-year capacity and there is no independent relationship to estimate total storage capacity. Moreover these relationships do not involve vulnerability performance criterion and are not verified for Malaysia Rivers. In this study two different reservoirs in Southern part of Peninsular Malaysia, Melaka and Muar, are analyzed through a Monte Carlo simulation approach involving performance metrics. Subsequently the storage capacity results of the simulation are compared with those of the well-known existing equations. It is observed that existing models may not predict total capacity appropriately for Malaysian reservoirs. Consequently, applying the simulation results, two separate regression equations are developed to model total storage capacity of study reservoirs employing time based reliability and vulnerability performance measures.

Keyword- over-year storage capacity, within-year storage capacity, total storage capacity, performance measures, reliability, vulnerability, Monte Carlo Simulation

I. INTRODUCTION

Traditionally, reservoir system planning studies are usually based on a single historic streamflow data record, often using critical sequence planning. Critical sequence planning focuses on the worst drought in the historic record on the hypothesis that future inflow sequences will not contain a more severe drought. However, this is unlikely to be the case. Besides, use of only the historic data record in water resource studies does not allow for the testing of alternative designs and policies against the range of sequences that are likely to happen in the future[1, 2]. Therefore, stochastic techniques for generating streamflow data that are widely used in developed countries are employed in this study rather than methods based on historical data [3, 4, 5].

The ability of existing and proposed water resource systems to operate satisfactorily under the wide range of probable future demands and hydrologic conditions is an important system characteristic [3, 6]. The likely performance of water resource systems is often measured and evaluated by performance indices which are based on the particular aspects of an unsatisfactory operation during drought periods [7]. An unsatisfactory operation is often described as a failure, which is defined as the inability of a reservoir system to provide the target demand during a given period [8]. These performance measures should be useful in the selection of reservoir system capacities, configurations, operating policies, and targets [9, 10, 11]. Hashimoto et al. (1982) presented performance indicators to measure the effectiveness of reservoir operations. The performance criteria were reliability (i.e. how often the system fails) and vulnerability (i.e. how severe the consequences of the failure may be). For instance reliability of 97% means that the reservoir is capable to satisfy the design demand entirely, during 97% of its operational period and vulnerability of 20% indicates that reservoir may not be able to fulfill up to 20% of its target demand during failure period.

The storage-yield analysis of reservoir systems could be divided into two general categories. The first group is probability matrix approach and is based on direct modeling of reservoir’s volume [12, 13]. The second group is critical period methods which consists of simulation and optimization approaches [2]. Among the mentioned methods only simulation approaches have enough flexibility to involve both reliability and vulnerability indices in the storage-yield analysis [3, 1]. Hence in this study modified Sequent Peak Algorithm (SPA) is employed which is capable of involving reliability and vulnerability metrics in the storage-yield analysis of reservoir systems [10].

The most important objective of planning of reservoir systems is to estimate the economical and realistic storage capacity that satisfies the target demand during the operational period with a specified reliability level

[1]. Therefore developing storage-yield-performance indices relationships based on Monte Carlo simulation would be very useful in preliminary stage of reservoir planning where detailed analysis is not necessary. This gives the designer a powerful tool to predict storage capacity for different demands and performance indices and an opportunity to select the most appropriate and economical option in a fraction of time that is required for detailed analysis [14]. The existing storage-yield-reliability (S-Y-R) relationships for reservoirs are mostly developed for over-year behavior (i.e. it takes more than one year for a full reservoir to become empty). In this case, only main annual streamflow characteristics such as mean, and Coefficient of Variation (C_V) play role in storage capacity estimation. Hence for this case it might be straightforward to develop (S-Y-R) relationships rather than total (i.e. within-year plus over-year) storage capacity which the number of involving parameters are so many and developing the relationship is complicated [15, 16]. Therefore existing models for total storage capacity are based on adjusting over-year capacity rather than modeling the total capacity independently. In this context storage capacity term is used similar to total storage capacity except when the type of capacity is mentioned.

A well-known relationship developed for modelling over-year storage capacity is as follows [17]:

$$K_O = \frac{z_g^2}{4(1-D)}(C_V)^2 \tag{1}$$

$$z_g = \frac{2}{\gamma}\left[\left(1+\frac{\gamma}{6}\left(z_f - \frac{\gamma}{6}\right)\right)^3 - 1\right] \tag{2}$$

$$z_f = \frac{f^{0.135} - (1-f)^{0.135}}{0.1975} \tag{3}$$

Where K_O is over-year storage capacity expressed as a ratio of Mean Annual Flow (MAF); D is demand expressed as a ratio of MAF; C_V is coefficient of variation (i.e. standard deviation divided by mean) of annual flow; γ is coefficient of skewness of annual flow; z_g is equivalent standardized gamma variable; z_f is standardized normal variable of f probability (decimal) of nonexceedance and 1-f is annual time based reliability.

Equation (1) is limited to over-year storage capacity and does not involve vulnerability index in estimating storage capacity. Moreover, this equation is only applicable for reservoirs that their annual streamflow data have gamma distribution function [17].

Another equation for adjusting over-year to total (i.e. over-year plus within-year) storage capacity is as follows [15]:

$$K_T = -0.222 + 0.322C_V + 0.6D + 1.025K_A \tag{4}$$

Where K_T and K_O are total and over-year storage capacity, respectively expressed as a ratio of Mean Annual Flow (MAF); D is demand expressed as a ratio of MAF and C_V is coefficient of variation of annual flow.

Equation (4) is calibrated based on simulation analysis using historical data that was carried out on 12 international rivers [15]. This equation is an adjusting relationship rather than a direct model to estimate total storage capacity and does not include performance indices. Thus, in this study after finding Storage Capacity by applying a Monte Carlo simulation approach in two reservoirs of Malaysia new regression equations are developed to model total storage capacity using both reliability and vulnerability indices. Since these two sites show different streamflow characteristics the equations are calibrated for each of them separately for obtaining high degree of accuracy.

II. METHODOLOGY

A. Catchment and Data

The study is carried out on two Malaysian rivers. Firstly, Melaka is the driest catchment in Malaysia which receives less than 2000 mm of rainfall annually. The second selected catchment is Muar which receives about 2400 mm rainfall annually. Melaka and Muar both enjoy a year-round tropical rainforest equatorial climate which is warm, humid and sunny [3]. The monthly streamflow data of the catchments are applied in this study to simulate total (i.e, within-year plus over-year) storage capacity. The brief characteristics of the catchments are presented in TABLE I. These sites are considered as standalone independent reservoirs in the study.

TABLE I
Characteristics of the study catchments

Site	River	Gauging station	Record length (years)	Catchment Area (Km^2)	Annual flow statistics				
					Mean (mm)	Mean (10^6 m^3)	C_V	Skew	ρ^*
1	**Melaka**	**Pantai Belimbing**	51 (1962-2012)	350	531	186	0.40	0.48	0.16
2	**Muar**	**Buluh Kasap**	47 (1966-2012)	3130	434	1359	0.48	2.03	0.18

Preliminary data analysis are carried out to ensure that the streamflow data possess appropriate statistical characteristics to be used in time series analysis. This involves double mass curve diagram which verifies data for homogeneity and consistency [18]. The data are also subjected to trend and run-test procedures to make sure that they are stationary and the result of a random and natural process [5, 19]. The fittest probability distribution function of data is determined using Probability Plot Correlation Coefficient (PPCC) test as Pearson III for both monthly and annual streamflow data [3, 20].

B. Synthetic generation of streamflow data

Realistic generation of streamflow scenarios should consider droughts that are more severe than historical ones. Therefore, appropriate data generation methods are applied in this study [21]. Data generation models for reservoir system analysis must preserve the essential statistical characteristics of historical streamflow data at both annual and monthly level. Hence, the combination of Auto Regressive Lag one (AR (1)) to generate annual flows and Valencia and Schaake (V-S) to disaggregate annual flows to monthly flows are applied in this study rather than using a single model to generate monthly flows directly like Thomas-Fiering [22, 23]. The AR (1) model can be expressed by the following equation:

$$q_{i+1} = \overline{q} + \rho(q_i - \overline{q}) + z_i s\sqrt{(1-\rho^2)} \tag{5}$$

Where q_{i+1} and q_i are the annual flows for the $(i+1)$th and ith years, respectively; $\overline{q}$ is the mean annual flows; z_i is the standardized normal random variable; s is standard deviation of annual flows and ρ is lag-1 serial correlation of annual flows.

In Equation (5) the annual streamflow data are first standardized and then normalized, so $\overline{q}$ = 0 and s = 1. The selected probability distribution function for annual flows is Pearson III. Hence to transform the standardized data to normalized data Wilson-Hilferty transformation is applied [2]. The normalized annual data are then disaggregated into monthly flows using V-S matrix model [3, 22]. The generated data are still standardized and normalized. Therefore they are transformed to the data that has Pearson III probability distribution using Wilson-Hilferty transformation and subsequently they are also converted from standardized data to ordinary monthly streamflow data. Finally, the synthetic streamflow data are generated employing combination of AR(1) and V-S models in 1000 sequences which each sequence is equal in length to the historical data.

C. Storage-yield-performance analysis of reservoir systems

The analysis of reservoir systems considering performance indices is carried out using modified Sequent Peak Algorithm (SPA) [24, 10]. This algorithm is capable of undertaking both time based reliability and vulnerability in simulating storage capacity of reservoir systems for specified demands [6, 11, 25]. The reservoir systems are simulated for 1000 sequences of synthetic monthly streamflow data generated according to Section 2.2. The analysis for every sequence is carried out assuming constant demands in all months of the year for 20%, 30%, 40%, 50%, 60%, 70%, and 80% of Mean Annual Flow (MAF). The combinations of time based reliabilities of 90%, 93%, 95%, 96%, 97%, 98%, 99% and 100% and the vulnerabilities of 0%, 5%, 10%, 15%, 20%, 25% and 30% are also undertaken in the simulation. Consequently 1000 sequences of storage capacities are estimated for each site corresponding to every combination of demand, reliability and vulnerability by modified SPA [3]. As it is clear, planning reservoirs for every case of reliability, vulnerability and demand requires applying a single value of storage capacity. Hence the average of 1000 sequences of capacities for every case is taken as the most appropriate estimate of storage capacity.

III. RESULTS AND DISCUSSIONS

A. Generated Sequences of Storage Capacities

The box plots notation developed by Tukey is applied to illustrate the empirical dispersion of storage capacities [26, 27]. To generalize the results storage capacity is standardized by dividing to Mean Annual Flow (MAF). Fig. 1 shows the empirical boxplots of standardized storage capacity of study sites for three different reliabilities and two demands of 30% and 70% of MAF in vulnerability of 30%. The demands of 30% and 70% of MAF usually represent within-year and over-year behaviors respectively. The boxplots depict maximum, minimum, 25, 50 and 75 percentiles of generated storage capacities. Generally the dispersions of storage capacities are appropriate for all the cases especially for high demand of 70% of MAF.

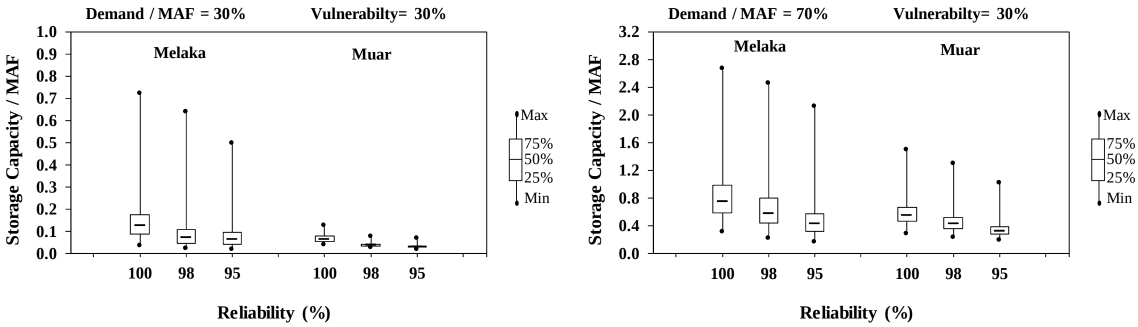

Fig. 1. Empirical box plots of storage capacity of study sites for different demands and reliabilities in vulnerability of 30%

B. Performance of existing models in estimating storage capacity

TABLE II exhibits the results of storage capacity of study reservoirs expressed as a ratio of Mean Annual Flow (MAF) obtained through simulation using synthetic data (K_S) and the results of Equation (1) (K_O) and Equation (4) (K_T) for study sites together with values of C = K_T / K_O in 100% reliability level for different demands. Simulation of reservoirs by modified SPA are carried out on monthly streamflow data herein. Hence the total (i.e. within-year plus over-year) storage capacity is obtained through the simulation and *Ks* estimates total storage capacity [1]. Equation (1) estimates over-year storage capacity and Equation (4) adjusts results of Equation (1) to obtain total storage capacity herein.

It is clear from TABLE II that compared to simulation results (K_S), Equation (4) mostly over-estimates total storage capacity in Melaka and Muar for all demands. Especially for low demands (i.e. the reservoir's behavior is usually within-year) the difference is much more evident. Hence Equation (4) together with Equation (1) may not be appropriate models to predict total storage capacity for Malaysian reservoirs particularly for low demands that the reservoir's behavior is mostly within-year.

Moreover the values of $C = K_T / K_O$ (i.e. results of Equation (4) divided by those of Equation (1)) should be practically applicable to distinguish the behavior of reservoir systems. (i.e., for high demands that the reservoir's behavior is mostly over-year the *C* ratio should be near to unity and for low demands that the behavior is within-year it should be far from unity) [28]. However according to the results in TABLE II, *C* ratio of high demands is far from unity and is mostly larger than *C* ratio for low demands. Thus, Equation (4) may not be able to adjust over-year storage capacity to total capacity appropriately for Malaysian reservoirs. Consequently, in this study according to Monte Carlo simulation results using modified SPA approach, new regression models are developed for two study sites separately to estimate total storage capacity for different reliability, vulnerability performance indices and demands.

TABLE II
Storage Capacity of Study Reservoirs as a Ratio of Mean Annual Flow through Different Methods together with *C* Ratio for Different Demands in 100% Reliability

Site 1	Method	Storage Name	Demand / MAF						
			0.2	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**
Melaka	Simulation	K_S	0.07	0.14	0.24	0.37	0.55	0.81	1.25
	Equation (1)	K_O	0.54	0.62	0.72	0.87	1.08	1.44	2.16
	Equation (4)	K_T	0.58	0.72	0.89	1.09	1.37	1.80	2.60
	*$C= K_T / K_O$		*1.07*	*1.16*	*1.23*	*1.26*	*1.27*	*1.25*	*1.20*
Site 2	**Method**	**Storage Name**	**Demand / MAF**						
			0.2	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**
Muar	Simulation	K_S	0.03	0.07	0.13	0.20	0.31	0.58	1.17
	Equation (1)	K_O	0.17	0.20	0.23	0.28	0.35	0.46	0.69
	Equation (4)	K_T	0.23	0.32	0.41	0.52	0.65	0.83	1.12
	*$C = K_T / K_O$		*1.33*	*1.60*	*1.78*	*1.87*	*1.88*	*1.79*	*1.62*

* Values of C ratio are in italic format

C. Modeling storage capacity of reservoir systems

1) Relationship between storage capacity and parameter m

There are some parameters that play significant role in total storage capacity of reservoir systems. These parameters can be obtained through correlation matrix methods [29, 28]. The parameters include Coefficient of Variation of annual flows (C_V), performance indices and standard demand parameter. Standard demand parameter (parameter *m*) can be obtained by following equation [30, 17]:

$$m = \frac{1 - D}{C_V} \tag{6}$$

Where *D* is demand expressed as a ratio of Mean Annual Flow (MAF) and C_V is the coefficient of variation of annual flows. Parameter *m* seems to be the most important variable in determining storage capacity of reservoir systems because it encapsulates both demand and C_V factors [3]. Hence for different reliability and vulnerability indices in both sites different regression relationships such as exponential, linear, logarithmic and power are tried between standardized storage capacity (i.e. storage capacity divided by MAF) and parameter *m*. It is observed that exponential function produces maximum R^2 when it is fitted on standardized storage capacities produced by Monte Carlo simulation. Fig. 2 shows the fitness of exponential function to the simulated standardized storage capacities in reliability = 96% and vulnerability= 15% for study sites as a sample. Consequently the relationship for estimating storage capacity (SC) as a function of parameter *m* can be expressed as follows:

$$\frac{SC}{MAF} = A.e^{mB} \tag{7}$$

Where *SC* is storage capacity; *MAF* is Mean Annual Flow and *m* is standard demand parameter (Eq. (6)). Coefficients of *A* and *B* are the variables that depend upon reliability and vulnerability indices. Equation (7) includes the demands of 20%, 30%, …, 80% of Mean Annual Flows which covers the required range of the demands that is usually applied in planning stage of reservoirs. Different values of coefficients of *A* and *B* together with their corresponding fitness values of R^2 are presented in TABLE III. As it is observed from this table all value of R^2 are between 0.99 and 1.00 that indicates the exponential relationship is very efficient in modelling total (i.e. within-year plus over-year) storage capacity.

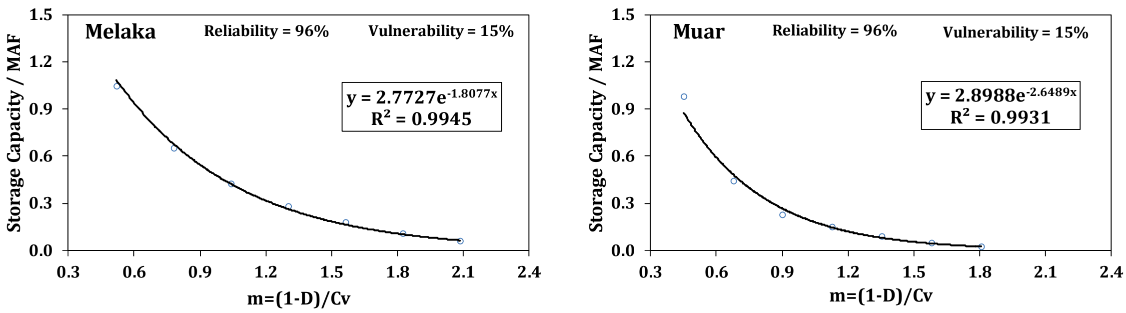

Fig. 2. Fitness of exponential relationship in modeling storage capacity as parameter *m* function for reliability of 96% and vulnerability of 15% in study sites

TABLE III
Coefficients of *A* and *B* together with Their Corresponding Values of R^2 for Different Reliabilities and Vulnerabilities for Study Sites

		Melaka			Muar				Melaka			Muar		
Rel.*	**Vul.****	**A**	**B**	**R^2**	**A**	**B**	**R^2**	**Vul.**	**A**	**B**	**R^2**	**A**	**B**	**R^2**
1.00	**0.00**	3.35	-1.76	0.99	3.57	-2.58	0.99	**0.00**	3.35	-1.76	0.99	3.57	-2.58	0.99
0.99		3.35	-1.79	0.99	3.59	-2.63	0.99		3.36	-1.86	0.99	3.64	-2.76	0.99
0.98		3.29	-1.79	0.99	3.49	-2.63	0.99		3.20	-1.90	0.99	3.41	-2.78	0.99
0.97		3.20	-1.78	0.99	3.37	-2.61	0.99		2.91	-1.88	1.00	3.08	-2.74	1.00
0.96	**0.05**	3.12	-1.77	0.99	3.28	-2.59	0.99	**0.20**	2.64	-1.84	1.00	2.79	-2.69	0.99
0.95		3.05	-1.76	0.99	3.21	-2.58	0.99		2.40	-1.79	0.99	2.59	-2.65	0.99
0.93		2.96	-1.74	0.99	3.08	-2.55	0.99		2.11	-1.72	0.99	2.23	-2.56	0.99
0.90		2.88	-1.73	0.99	2.93	-2.52	0.99		1.87	-1.65	0.99	1.87	-2.44	0.99
0.99		3.35	-1.81	0.99	3.62	-2.68	0.99		3.36	-1.89	0.99	3.63	-2.78	0.99
0.98		3.24	-1.83	0.99	3.45	-2.68	0.99		3.19	-1.94	0.99	3.40	-2.82	0.99
0.97		3.08	-1.81	0.99	3.23	-2.65	0.99		2.85	-1.92	1.00	3.05	-2.79	1.00
0.96	**0.10**	2.93	-1.79	0.99	3.06	-2.61	0.99	**0.25**	2.54	-1.87	1.00	2.72	-2.74	1.00
0.95		2.79	-1.76	0.99	2.93	-2.59	0.99		2.25	-1.81	1.00	2.49	-2.69	1.00
0.93		2.63	-1.73	0.99	2.71	-2.54	0.99		1.92	-1.72	0.99	2.10	-2.59	0.99
0.90		2.49	-1.70	0.99	2.46	-2.47	0.99		1.64	-1.64	0.99	1.69	-2.46	0.99
0.99		3.35	-1.84	0.99	3.63	-2.72	0.99		3.37	-1.91	0.99	3.61	-2.80	0.99
0.98		3.21	-1.86	0.99	3.42	-2.73	0.99		3.20	-1.99	0.99	3.39	-2.85	0.99
0.97		2.98	-1.84	0.99	3.14	-2.69	0.99		2.83	-1.96	1.00	3.03	-2.83	1.00
0.96	**0.15**	2.77	-1.81	0.99	2.90	-2.65	0.99	**0.30**	2.47	-1.91	1.00	2.69	-2.79	1.00
0.95		2.58	-1.77	0.99	2.73	-2.61	0.99		2.14	-1.84	1.00	2.44	-2.74	1.00
0.93		2.35	-1.72	0.99	2.43	-2.54	0.99		1.76	-1.74	0.99	2.01	-2.64	1.00
0.90		2.15	-1.67	0.99	2.12	-2.45	0.99		1.45	-1.63	0.99	1.56	-2.48	1.00

*Reliability, **Vulnerability

2) Regression equations to model storage capacity

It is required to express coefficients of A and B in Equation (7) as a function of reliability and vulnerability indices to develop regression equations for modelling Storage Capacity. Hence the coefficients of A and B can be expressed as follow:

$$A = a_1 + b_1.R_e + c_1.V_u \tag{8}$$

$$B = a_2 + b_2.R_e + c_2.V_u \tag{9}$$

Where R_e is the reliability indices between 0.90 and 1.00 and V_u is vulnerability indices between 0.00 and 0.30.

The coefficients of a_1, b_1, c_1, a_2, b_2 and c_2 are obtained through multiple regression analysis by employing the method of least squares for each two sites separately using coefficients of *A* and *B* corresponding to different reliabilities and vulnerabilities that are presented in TABLE III. Each of these equations is calibrated for 48 cases for Melaka and Muar rivers separately (8 (reliabilities) × 6 (vulnerabilities)). The estimated coefficients and t-statistics are presented in TABLE IV. The t-statistics involve t-ratios and critical t-ratios. The t-ratios are obtained through dividing the estimated coefficient by their corresponding standard errors. The t-ratios show the significance of corresponding coefficients in regression analysis and their absolute values should be greater than critical t-ratio to be statistically effective in regression analysis. Critical t-ratio can be obtained by specified degree of freedom (DF) of regression analysis and assuming probability level (α) through the relevant statistical table. In this analysis DF = 45 and α = 0.05 therefore the critical t-value is 2.01. It can be observed that absolute value of all t-ratios in TABLE IV are greater than critical t-ratio (2.01) which implies that both reliability and vulnerability indices are significant in the regression analysis.

TABLE IV
Estimated Regression Coefficients and T-Statistics

Site	**Coef.***	**A**			**Coef.**	**B**		
		Estimate	**t-value**	**Critical t-value**		**Estimate**	**t-value**	**Critical t-value**
Melaka	$\mathbf{a_1}$	-9.24	-8.06	2.01	$\mathbf{a_2}$	0.29	2.37	2.01
	$\mathbf{b_1}$	12.84	10.93	2.01	$\mathbf{b_2}$	-2.10	-9.53	2.01
	$\mathbf{c_1}$	-1.76	-4.80	2.01	$\mathbf{c_2}$	-0.51	-7.35	2.01
Muar	$\mathbf{a_1}$	-11.25	-10.23	2.01	$\mathbf{a_2}$	0.11	2.52	2.01
	$\mathbf{b_1}$	15.08	13.37	2.01	$\mathbf{b_2}$	-2.74	-12.38	2.01
	$\mathbf{c_1}$	-1.50	-4.26	2.01	$\mathbf{c_2}$	-0.78	-11.34	2.01

*Coefficient

Summary statistics of regression analysis is presented in TABLE V. The R^2 is the coefficient of determination of regression analysis which is suitable for all the cases in the analysis. SEE is standard error estimate of coefficients of *A* and *B*. F-stat is F-statistics which is high enough for all the cases. The degree of freedom of regression analysis is DF which is 45 for all the cases and finally F-dist is the probability that a higher value of F-stat is occurred by chance and as it is seen, F-dist values are 0.00 for all the cases in the analysis which implies that the high magnitudes of F-stat have not occurred by chance and are valid. Consequently, according to TABLE IV and V it is concluded that the regression analysis is statistically efficient enough to estimate coefficients of *A* and *B* for the study sites.

TABLE V
Summary Statistics of Regression Analysis

	Melaka		**Muar**	
	A	**B**	**A**	**B**
$\mathbf{R^2}$	0.81	0.72	0.85	0.83
SE	0.24	0.05	0.23	0.05
F-stat	94.2	57.0	125.2	109.6
DF	45	45	45	45
FDIST	0.00	0.00	0.00	0.00

3) Performance of regression models to estimate storage capacity

Having performed the regression analysis, calibrating the storage capacity equations and checking the efficiency of the analysis statistically, it is important to evaluate the performance of these equations in predicting storage capacity. The evaluation is performed by comparison between predicted and observed results of reservoir simulation. The storage capacity equations for Melaka and Muar are as follow:

$$\frac{SC}{MAF}(Melaka) = (-9.24 + 12.84R_e - 1.76V_u) \times e^{m(0.29 - 2.10R_e - 0.51V_u)} \tag{10}$$

$$\frac{SC}{MAF}(Muar) = (-11.25 + 15.08R_e - 1.50V_u) \times e^{m(0.11 - 2.74R_e - 0.78V_u)} \tag{11}$$

Where, SC is storage capacity in million cubic meters, MAF is Mean Annual Flow in million cubic meters, *m* is standardized demand parameter, *Re* is time-based reliability indices between 0.90 and 1.00 and *Vu* is vulnerability indices between 0.00 and 0.30.

The performance of Equations (10) and (11) are shown in Fig. 3. The simulation of storage capacity executed for each site consists of 336 cases (8 (reliabilities) × 6 (vulnerabilities) × 7 (demands)) where each case represents a scatter plot in Fig. 3. It is observed that for both sites the points are scattered closely around y = x line which means that the observed results from the simulation are accurately reproduced by the estimated results from regression equations. The correlation coefficient between observed SCs and estimated SCs are 0.9946 and 0.9924 for Melaka and Muar rivers, respectively and also the standard error in estimating SCs are 0.0374 and 0.0375 for two sites, respectively which generally confirms the very good performance of regression equations in modeling Storage Capacity.

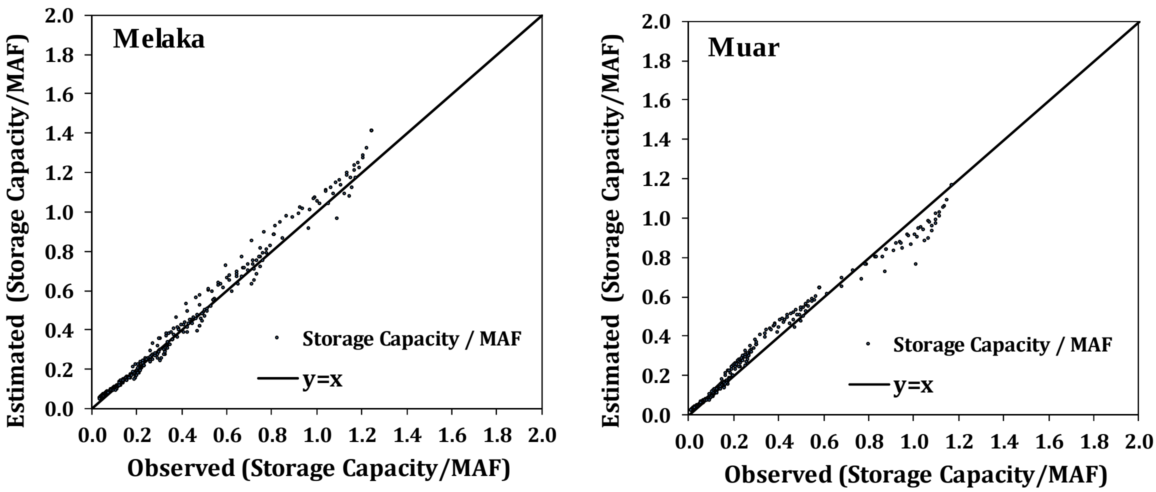

Fig. 3. Performance of regression equations in modeling of storage capacity

IV. CONCLUSION

Prediction relationships for total storage capacity in Malaysia is beneficial because they can be used in preliminary stage of planning reservoir systems where detailed analysis is not necessary. Moreover, these relationships can be utilized in other sites with similar annual streamflow characteristics especially coefficient of variation and skewness where sufficient streamflow data for the analysis of reservoir systems is unavailable.

The main specific results of this study are as follow:

A. Existing models may not predict total storage capacity for reservoirs in Melaka and Muar appropriately even in 100% reliability level. Hence it is necessary to develop regression equations to model total capacity for these sites.

B. The Storage Capacity equations are developed for Melaka and Muar rivers individually because these two sites have different hydrological characteristics and developing a single equation for these two sites may decrease the accuracy. However, these equations can be applied for any other sites in Malaysia provided that their main annual streamflow characteristics especially Coefficient of Variation and Skewness are close to Melaka and Muar.

C. The new concept of predicting the storage capacity is the introduction of the reliability and vulnerability indices in the regression equations. Consequently this gives the water resources planner an opportunity to control the amount of deficit during failure period and to provide an alternative water resource.

D. The regression equations are calibrated based on Monte Carlo simulation results which can simulate probable droughts that are more severe than historical droughts during reservoirs operational period.

E. The storage capacity predicated from regression equations reproduce appropriately the observed storage capacity that obtained from Monte Carlo Simulation. This is promising because there are currently a few relationships to estimate total storage capacity.

F. It is beneficial to develop regression models to predict storage capacity for other sites in Malaysia during planning stage using Monte Carlo Simulation results employing reliability and vulnerability performance indices. Therefore as an extension to this study it is recommended to develop similar storage capacity equations for other sites and to generalize these equations for other hydrological regions in Malaysia.

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