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Limiting Parameters for Supporting Performance Index Assessment of Multi-Purpose Reservoir Storage Capacity

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Abstract: At present, the evaluation of reservoir storage capacity is primarily focused on the capacity for water supply and has not taken into account the capacity for flood storage. In addition, the performance assessment of reservoir storage capacity has not been classified as very good, good, good enough, and not good. This research investigates the factors that influence the performance assessment of reservoir storage capacity. The research locations are in 16 dams spreading across some Indonesian islands. There are dams that have been developed and are in the stage of reservoir filling. The methodology comprises an assessment of the suitability of the reservoir storage capacity indicator through the employment of PLS-SEM. This entails the following steps: determining the variables and constructing the model, collecting data, conducting data analysis, specifying the model, estimating the model, evaluating the model, interpreting the model, validating and retesting, arranging the conclusion, and providing a final interpretation. The results show that the variables that influence are the coefficient of discharge variation (Cv), water demand for utilization (D), reservoir capacity demand for flood storage (Df), and carry-over reservoir storage capacity (K_A). The influence of the four variables on multi-purpose reservoir storage capacity has not been extensively analyzed in the assessment of the performance index for such reservoirs.

Keywords: reservoir storage capacity, performance index, partial least squares structural equation modeling.

综合利用水库库容性能指标评估支持性限制参数

摘要：目前，水库库容评估主要侧重于供水能力，并未考虑洪水储存能力。此外，水库库容性能评估尚未被划分为非常好、好、足够好和不好。本研究调查了影响水库库容性能评估的因素。研究地点分布在印度尼西亚一些岛屿上的 16 座水坝。有些水坝已经开发并处于蓄水阶段。该方法包括通过使用偏最小二乘扫描评估水库库容指标的适用性。这需要以下步骤：确定变量并构建模型、收集数据、进行数据分析、指定模型、估计模型、评估模型、解释模型、验证和重新测试、整理结论并提供最终解释。结果表明，影响的变量是流量变异系数(Cv)、用水需求(D)、洪水储存的水库容量需求(Df)和结转水库库容(KA)。在综合利用水库性能指标评估中，尚未广泛分析上述四个变量对此类水库库容的影响。

关键词：水库库容，性能指标，偏最小二乘结构方程建模。

1. Introduction

The performance of the reservoir storage capacity in the design stage is based on the design of the reservoir lifetime. Therefore, in the design of a reservoir, we analyze the number of sediments that enter the reservoir during its lifetime. The reservoir lifetime is determined based on the duration of dead storage containing sediment. However, the effectiveness of dams as a water supply can be assessed by calculating the ratio between the storage volume and the average inflow and taking into account factors such as the low baseflow, increasing water demand, river flow discharge, and the operational pattern of the reservoir, which may not be consistent [1]. Additionally, decisions to increase the water level depth (TMA) for hydroelectric power facilities must also be considered [2]. Dams have the potential to serve as effective flood control mechanisms, working as flood peak reducers [3, 4] during the rainy season. To achieve this, it is essential to evaluate factors such as the ratio of storage volume to inflow average, the capacity of the spillway and outlet, and the reservoir operation pattern [5]. It is necessary to determine the maximum TMA during both the rainy and dry seasons, decrease the reservoir TMA, fill back the reservoir, and select a dam location in a high rainfall area.

The present state of affairs is such that the evaluation of reservoir storage capacity has been devised by McMahon et al. This evaluation consists of the performance curve for the reservoir storage capacity without failure and the regression formula for the reservoir's total capacity (K_T) [6]. However, the capacity for reservoir storage has been established in 15 rivers across South Africa, the USA, England, Australia, and Turkey, with 12 rivers designated for calibration and three for verification. The regression formula of reservoir storage capacity performance uses the parameter of discharge variation coefficient (C_V), over-year storage capacity (K_A), and water demand (D). Reservoir performance is assumed without failure if based on the value of C_V, the intersection of X (ratio: K_T/inflow) and Y (ration: D/inflow) is in the boundary of the monthly and yearly curves.

In Malaysia, the reservoir storage capacity performance model serves a valuable purpose during the initial planning phase of reservoir systems. While detailed analysis may not be required at this stage, the model remains a useful tool for evaluating the capacity of reservoir systems [7]. To assess the reservoir capacity, an empirical method is employed, and the limits of the reservoir capacity are determined based on the behavior and capacity that are permissible in North America, the South Pacific, Europe, and Africa [8, 9]. Then, the regression formulation is developed to forecast yearly capacity during the design phase of reservoir construction [10].

The use of reservoir storage capacity performance assessment needs to be researched if it is applied in Indonesia; it is due to the difference in catchment characteristics. The current method of evaluating the storage capacity of a reservoir is centered around its ability to provide water supply [11]. However, it has yet to examine the capacity for flood storage. This study examines the variables that impact the evaluation of reservoir storage capacity based on its performance index.

2. Materials and Methods

2.1. Research Locations

The research was conducted across 16 dams situated in Indonesian islands, for those under construction, those developed, and those filled with water. Fig. 1 presents the research location plan.

Fig. 1 Research location plan (Own study)

2.2. Methodology

To evaluate the performance measure of a multi-purpose reservoir's storage capacity, the following steps are taken:

1. Variables such as Cv, D, and K_A are utilized.
2. The design flood is analyzed for several return periods.
3. The ratio between the volume of floods with various return periods and MAF is calculated.
4. The ratio of MAF for floods with different return periods is determined.
5. The reservoir storage capacity without failure (K_T) is simulated.
6. The demand for sufficient water storage during a long drought period (carry-over demand, K_A) is simulated.
7. The reservoir storage capacity for flood storage with multiple return periods (D_f) is simulated.
8. The scoring data for the assessment of multi-purpose reservoir storage capacity are arranged.
9. The suitability of the reservoir storage capacity assessment indicator is analyzed using partial least squares structural equation modeling (PLS-SEM).

Table 1 presents the characteristics of the research locations.

Table 1 Characteristics of the research locations (Own study)

No.	Location	Island	Watershed area (km^2)	Depth of the dam (m)	Total volume (million m^3)	Yearly inflow (million m^3)	NWL: surface area (ha)	HWL: surface area (ha)	Irrigation area (ha)	Raw water (l/s)	Hydropower (MW)	Flood reduction (million m^3)
1	Beringin Sila	Sumbawa	61.50	80.0	27.46	68.72	125.02	138.17	2.400	76	1.40	90.37
2	Bintang Bano	Sumbawa	212.00	72.0	65.84	237.43	130.00	153.00	6.696	555	9.00	21.13
3	Pandanduri	Lombok	64.51	42.0	29.69	75.57	316.21	330.45	5.168	50	-	-
4	Titab	Bali	82.90	77.8	12.80	137.35	65.74	81.65	1.795	35	1.50	12.79
5	Sidan	Bali	64.58	68.0	3.82	53.20	21.96	25.63	4.595	2140	0.65	-
6	Rotiklot	Timor	11.69	42.0	2.67	9.01	18.28	23.30	139	40	-	-
7	Temef	Timor	554.21	53.0	69.97	431.07	85.96	297.78	4.800	131	2.00	-
8	Marangkayu	Kalimantan	134.31	14.4	12.30	258.84	454.94	720.47	4.500	45	1.35	-
9	Lolak	Sulawesi	72.83	58.0	16.10	96.31	101.06	105.21	2.214	500	2.43	-
10	Kuwil	Sulawesi	426.83	77.0	23.37	463.76	142.50	173.50		4320	1.30	146.60
11	Pamukkulu	Sulawesi	89.45	65.5	97.35	147.05	421.50	475.00	6.430	200	2.50	151.00
12	Batutegi	Sumatera	429.57	122.0	690.00	412.71	2.100	2.500	55.373	0	2x14	92.00
13	Keureuto	Sumatera	239.10	74.0	216.0	328.27	896.39	1,006.11	9,420	500	6.34	12.39
14	Bendo	Jawa	130.54	74.00	51.33	187.39	170.57	188.79		370	1.56	0.30
15	Kedunglanggar	Jawa	102.40	54.0	28.33	335.00	116.88	133.59	948	450		
16	Songputri	Jawa	1.77	25.0	0.51	4.18	10.08	10.65	148	75		
	Indonesia	Range	1.77–554.21	14.4-122	0.51-690	4.18-463.76	10.08-2.100	10.65-2.500	139-55.373	40-4320	0.65-28	0.30-151

2.3. Reservoir Storage Capacity

The capacity of a reservoir to store water (storage capacity) can be divided into three zones [12]:

1. The dead storage zone serves as a collection point for sediment.
2. The functional storage capacity is employed for the preservation of water sources, including providing untreated water for irrigation purposes, and other similar applications. Reservoir utilization in storage

conservation can fulfill the reservoir's effective capacity [13, 14].

3. The flood control capacity of a reservoir is intended to hold excess water to reduce the impact of flooding and mitigate potential damage [15].

Fig. 2 shows the characteristics of the reservoir storage.

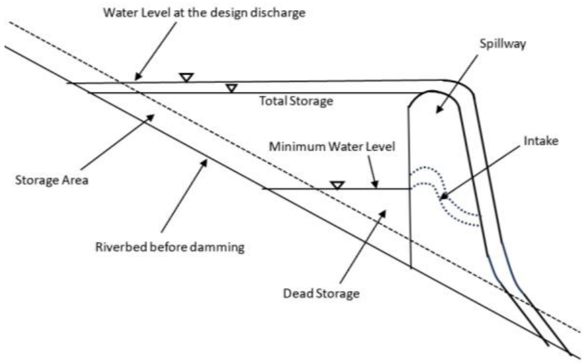

Fig. 2 Reservoir storage characteristics (Own study)

The assessment of storage capacity is frequently hampered by errors due to the absence of a precise water availability analysis [16, 17], which is heavily influenced by the fluctuations in climate change and the length of the data utilized. To reduce the errors, the variability in water availability data can be determined [18]. A flowchart of the study is presented in Fig. 3.

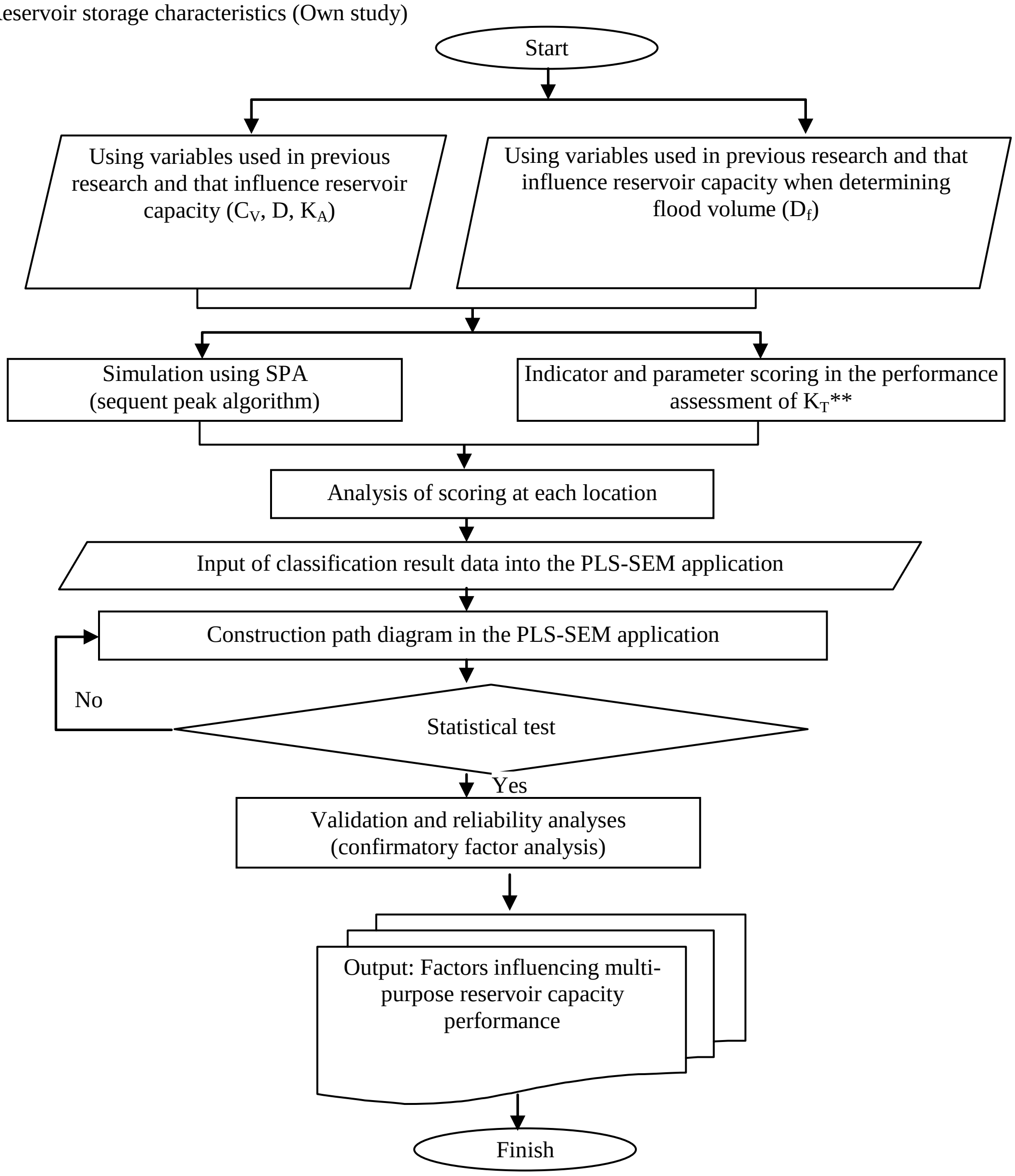

Fig. 3 Flowchart of reservoir storage capacity performance factors (Own study)

Given the literature review above, the following hypothesis can be proposed: the variables that influence the performance assessment of reservoir storage capacity are the coefficient of discharge variation (Cv), water demand for utilization (D), reservoir capacity demand for flood storage (Df), and carry-over reservoir storage capacity (K_A).

3. Results and Discussion

3.1. Factors Influencing Multi-Purpose Reservoir Storage Capacity

This study increases the capacity for storing water in multi-purpose reservoirs by incorporating the storage capacity for floods. The methodology employed in SEM involves the following approaches:

1. *Confirmatory strategy [19]:* A single model is developed and then subjected to empirical data to be statistically tested. This test either confirms or rejects the model.

2. *Model competition strategy:* An alternative model is proposed and evaluated against a group of selected empirical data that is most relevant.

3. Model development strategy: An initial model is proposed, and empirical data are collected. If the initial model is not suitable for the available data, it is modified and tested again with the same data. This process is repeated until a suitable model is found that is well-suited to the data and the characteristics of each parameter.

The fundamental premise of SEM is rooted in the estimation of parameters in SEM, which is typically grounded in the maximum likelihood method. This method satisfies several assumptions, including those listed below:

1. The number of samples must be large (asymptotic). Sample size plays an important role in interpreting SEM results. The size of the sample serves as the foundation for calculating the sampling error. In conducting SEM analysis, it is imperative to satisfy a fundamental premise that the number of samples meeting the analysis criteria must be at least five times the number of variables [20].

2. Distribution of multivariate normal variables: To avoid bias in data analysis, it is crucial that the data analyzed in SEM are normally distributed. Data are considered normal when the multivariate cr is between -2.58 and 2.58. To address non-normal distributions, a large number of samples may be used to manipulate the data. Screening for normality is an initial step conducted for each multivariate analysis. If the data are normally distributed, the residuals will also be normally distributed and independent.

3. Measuring the scale of a continuous variable (interval) is a crucial aspect of variable measurement in SEM analysis. Ordinary variables that are assumed to be continuous must be treated in this context. When it comes to measuring a latent variable, the Likert scale with five categories is commonly used as an indicator. The correlation produced by the Likert scale is very high, at 0.92, suggesting continuity.

3.2. Variable Measurement Determined by Variable Classification Categorizing Divisions Based on a Set of Criteria

The classification of the discharge variation coefficient (C_V) into five categories can be accomplished by evaluating the level of data variation. The categories that may be used are as follows:

✓ Very good: $C_V < 10\%$
✓ Good: $10\% \leq C_V < 20\%$
✓ Good enough: $20\% \leq C_V < 30\%$
✓ Moderate: $30\% \leq C_V < 40\%$
✓ Bad: $C_V \geq 40\%$

Classification of water storage capacity for extended drought periods (carry-over storage, Ka) can be categorized into eight groups by assessing the extent of data variation. The categories that may be used are as follows:

✓ Very small: capacity of less than 30 million cubic meters

✓ Small: capacity ranging from 30 million to 100 million cubic meters

✓ Moderate: capacity ranging from 100 million to 200 million cubic meters

✓ Moderate-big: capacity ranging from 200 million to 300 million cubic meters

✓ Big-small: capacity ranging from 300 million to 500 million cubic meters

✓ Big: capacity ranging from 500 million to 800 million cubic meters

✓ Very big: capacity ranging from 800 million to 1.2 milliard cubic meters

✓ Very-very big: capacity of more than 1.2 milliard cubic meters

The categorization of irrigation water demand or raw water (D) into eight categories can be accomplished by evaluating the degree of data variation. The categories that may be used are as follows:

✓ Very-very low: capacity less than 10 million cubic meters

✓ Very low: capacity ranging from 10 million to 20 million cubic meters

✓ Low: capacity ranging from 20 million to 30 million cubic meters

✓ Moderate-low: capacity ranging from 30 million to 40 million cubic meters

✓ Moderate: capacity ranging from 40 million to 60 million cubic meters

✓ Moderate-high: capacity ranging from 60 million to 80 million cubic meters

✓ High: capacity ranging from 80 million to 100 million cubic meters

✓ Very high: capacity ranging from 100 million to 120 million cubic meters

✓ Very-very high: capacity ranging from 120 million to 150 million cubic meters

✓ Extreme: capacity of more than 150 million cubic meters

Categorizing the flood storage capacity (Df) into six groups can be achieved by evaluating the degree of data fluctuation. The categories that may be used are as follows:

- Very less: Flood storage is for less than a 2-year return period.
- Less: Flood storage is for a return period between 2 and 5 years.
- Low: Flood storage is for a return period between 5 and 10 years.
- Moderate: Flood storage is for a return period between 10 and 20 years.
- Big: Flood storage is for a return period between 20 and 25 years.
- Very big: Flood storage is for a return period of over 25 years.

3.3. PLS-SEM Initial Conditions

The initial path model in PLS-SEM is a critical prerequisite to the PLS-SEM analysis as it establishes the links between the observed variables. This part involves two main stages: formulation and evaluation of the model.

Model formulation is a crucial aspect of analyzing the relationship between observed variables. It involves identifying endogenous and exogenous variables. Endogenous variables are those influenced by the other variables in the model, while exogenous variables are not influenced by the other variables. Model formulation also entails identifying the relationship between variables, which is represented by a path. Model evaluation, on the other hand, assesses how well the model fits the observed data. This evaluation involves two components: 1) path analysis, which examines the relationship between variables in the initial path model. In PLS-SEM, this relationship is expressed as a path between variables. Path analysis enables researchers to determine the significance of the paths and measure the strength of the relationship between variables; 2) testing for goodness of fit is necessary to measure how well the model can estimate the variability in the data. One of the tests used for this purpose is R-squared (R^2).

The PLS-SEM initial path model is a significant initial step in SEM analysis as it offers a framework for comprehending the connections between the observed variables. By improving and evaluating the initial path model, we can understand the system dynamics that are studied and make stronger conclusions about the inter-variable relationships.

Fig. 4 presents the simulation results for the outer loading value, Fig. 5 presents the initial path models of PLS-SEM, and Table 2 presents the outer loading as the result of PLS-SEM analysis.

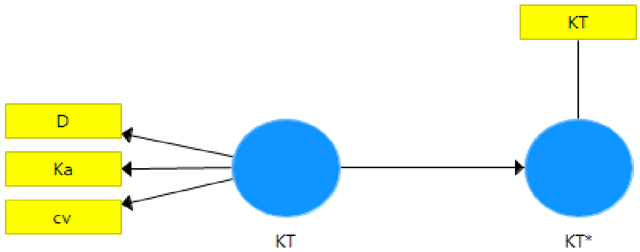

Fig. 4 Simulation results for the outer loading values (Own study)

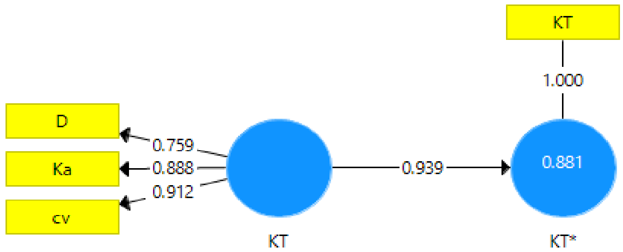

Fig. 5 Initial path model of PLS-SEM (Own study)

Table 2 Outer loading (Own study)

	KT*_	KT_	Information
D	1.000	0.759	0.759 > 0,7 ➔ valid
Ka		0.888	0.888 > 0,7 ➔ valid
Cv		0.912	0.912 > 0,7 ➔ valid

Notes: D - demand (ratio of demand/MAF); KT* - performance of reservoir storage capacity (ratio of reservoir storage capacity/MAF); KT - reservoir storage capacity (ratio of reservoir storage capacity/MAF); Ka – carry-over storage (ratio of carry-over water capacity enough for a long drought period/MAF); Cv - coefficient of discharge variation

Outer loading shows the correlation between variables and latent variables. If a variable has outer loading < 0.7, the variable is eliminated. In this case, all variables have outer loadings > 0.7, so all variables are valid. Table 3 presents the construct variables and validity.

Table 3 Construct reliability and validity (Own study)

	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
KT*_	1.000	1.000	1.000
KT_	0.866	0.601	0.732
Explanation	Cronbach's alphas indicate the consistency of indicators when measuring the construct. The minimum value boundary of Cronbach's alpha is 0.7. The Cronbach's alpha of the simulation result is 0.866 > 0.7. This indicates that the indicator is consistent in measuring the construct.	Composite reliability measures the dependability of each indicator in relation to the establishment of a latent construct. The boundary of consistent composite reliability > 0.6. The simulation result shows composite reliability = 0.601 > 0; it expresses that the indicator is consistent or valid.	AVE determines whether each indicator can explain the variable or not. It is considered that the boundary value can explain the variables if AVE > 0.5. The simulation result shows AVE value = 0.732 > 0.5; it shows that the indicators are convergently valid.

3.4. Bootstrapping

Bootstrapping is a statistical model that is generally used in some analysis in PLS-SEM. In the PLS-SEM context, bootstrapping is used to estimate the uncertainty of model parameters and evaluate the significance of statistics from the paths identified in the model. Four aspects are needed to be attended to in bootstrapping: parameter estimation, interval confidence, significance test, and non-parametric.

Estimation of parameters in bootstrapping involves generating numerous bootstrap samples from the observed data. Subsequently, each bootstrap sample is utilized to derive parameter estimates in the PLS-SEM model. Through this process, bootstrapping contributes to the creation of a sampling distribution for parameter estimation, which can lead to more precise population parameter estimates. Upon acquiring the parameter estimation from the bootstrap sample, the technique of bootstrapping can be employed to evaluate the confidence interval for each parameter. This confidence interval delivers information regarding the uncertainty associated with parameter estimation and supplies an approximation of how much the actual parameter value may differ from the estimated value. Bootstrapping can also be used to test statistical significance from identified paths in the PLS-SEM model. By comparing the sampling distribution from the parameter estimation with zero (no effect) using the bootstrap method, the researchers can determine whether the paths are significantly different from zero. Ensuring a non-parametric assumption about the statistical distribution of the data is not a prerequisite for bootstrapping. This makes bootstrapping very flexible and can be used in various situations, primarily when the data distribution assumption cannot be fulfilled.

Employing bootstrapping in PLS-SEM allows researchers to attain more dependable parameter estimation, assess the statistical significance of the model, and generate supplementary information regarding the uncertainty of the analysis outcomes.

Fig. 6 presents the simulation results of the bootstrapping, and Table 4 presents the path coefficients of the bootstrapping.

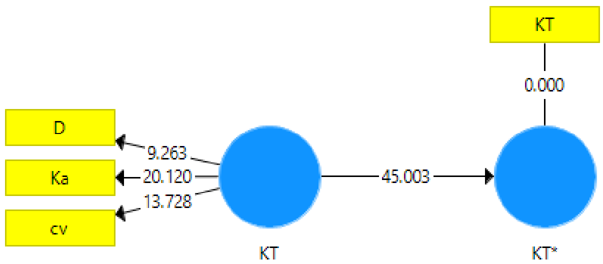

Fig. 6 Bootstrapping simulation results (Own study)

Table 4 Path coefficients of bootstrapping (Own study)

	T Statistics (|O/STDEV|)	P Values	Information
D <- K_T_	9.263	0.000	T statistic > 2 ➔ significant P value < 0.05 ➔ significant The D variable plays an important role in influencing K_T.
K_T <- K_T*_			
Ka <- K_T_	20.120	0.000	T statistic > 2 ➔ significant P value < 0.05 ➔ significant The Ka variable plays an important role in influencing K_T.
cv <- K_T_	13.728	0.000	T statistic > 2 ➔ significant P value < 0.05 ➔ significant The Cv variable plays an important role in influencing K_T.

According to the simulation outcomes, the initial variables (C_V, Ka, and D) exert a significant impact on K_T under appropriate conditions.

3.5. PLS-SEM Recommendation Conditions

In PLS-SEM, the simulation of outer loading is a method used to assess the impact of additional factors or variable deletion on the constructed model. It helps researchers understand how the inclusion or exclusion of certain variables can influence model construction and interpretation of results. The addition of variables in outer loading simulation can provide the following benefits: 1) increasing accuracy; 2) evaluating reliability; 3) testing hypotheses; 4) exploring the model.

By adding more variables, the model can become more accurate in explaining the relationships between the observed variables. It can occur if the additional variables have strong relationships with the other variables in the model. Adding more variables can help evaluate construct reliability. This is performed by observing how the additional variables contribute to the composite reliability or latent variable in the model. In some cases, researchers may be interested in evaluating additional hypotheses or digging more into certain aspects of the phenomenon under study. By adding more relevant variables, researchers can perform additional analyses to test these hypotheses. Outer loading simulation may also serve as an investigative tool for assessing the extent to which the established model accurately reflects the phenomena under examination. Through experimenting with various variable configurations, researchers can pinpoint the optimal model that best fits the existing data and theoretical frameworks.

By carefully considering the benefits and consequences of additional variables in outer loading simulation, researchers can maximize the validity and use of the developed model in PLS-SEM analysis. Fig. 7 presents the simulation outcomes of outer loading PLS-SEM under recommendation conditions, and Table 5 provides the recommendations for outer loading PLS-SEM.

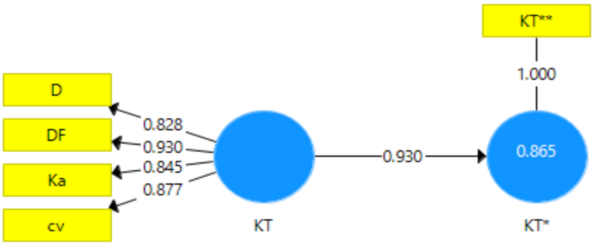

Fig. 7 Simulation results of outer loading PLS-SEM under recommendation conditions (Own study)

Table 5 Recommendations for outer loading PLS-SEM (Own study)

	KT*_	KT_	Explanation
D	1.000	0.828	0.828 > 0.7 ➔ valid
DF		0.930	0.930 > 0.7 ➔ valid
KT**			
Ka		0.845	0.845 > 0.7 ➔ valid
cv		0.877	0.877 > 0.7 ➔ valid

Outer loading shows the correlation between variables and latent variables. If a variable has outer loading < 0.7, the variable must be eliminated. In this case, all variables have outer loadings > 0.7 (Fig. 6 and Table 5); the variable combinations of C_V, D, D_f, and Ka can be used for further modeling. Table 6 presents the construct reliability and validity.

Table 6 Construct reliability and validity [19]

	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
KT*_	1.000	1.000	1.000
KT_	0.707	0.756	0.759
Explanation	Cronbach's alphas indicate the consistency of indicators when measuring the construct. The minimum value boundary of Cronbach's alpha is 0.7. The Cronbach's alpha of the simulation result is 0.707 > 0.7. This indicates that the indicator is consistent in measuring the construct.	Composite reliability refers to the degree of dependability of each indicator when contributing to the emergence of a latent construct. The boundary of consistent composite reliability > 0.6. The simulation result shows that composite reliability = 0.756 > 0; the indicator is consistent or valid.	AVE clarifies that each indicator has the potential to explain a variable or not. The threshold for determining whether an assumed boundary value can elucidate the variables is when AVE > 0.5. The simulation result shows AVE value = 0.759 > 0.5; it shows that the indicators are convergently valid.

3.6. Bootstrapping Validation

The findings of the bootstrapping simulation and the path coefficient analysis offer insights into the dependability and statistical significance of the proposed model. The evaluation is based on the reliability of model parameters, confidence intervals, statistical significance, and hypothesis testing. Utilizing the outcomes of bootstrapping simulations and path coefficients in PLS-SEM analysis, researchers can draw more robust conclusions regarding the dependability of the model, the significance of inter-variable relationships, and the broader interpretation of the analysis's results.

Fig. 8 presents the simulation results of recommendation bootstrapping, and Table 7 presents the path coefficients of the bootstrapping.

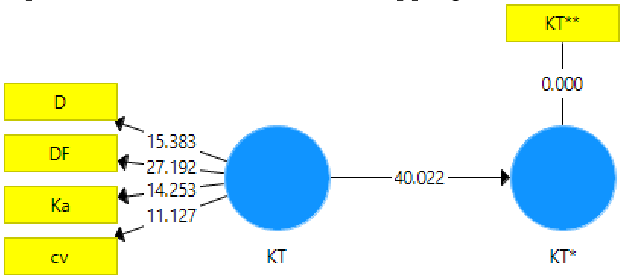

Fig. 8 Simulation results of recommendation bootstrapping (Own study)

Table 7 Path coefficients of bootstrapping [21]

	T Statistics (|O/STDEV|)	P Values	Information
D <- K_T_	15.383	0.000	T statistic > 2 ➔ significant P value < 0.05 ➔ significant The D variable plays an important role in influencing K_T.
DF <- K_T_	27.192	0.000	T statistic > 2 ➔ significant P value < 0.05 ➔ significant The Df variable plays an important role in influencing Kt.
KT <- K_T*_**			
Ka <- K_T_	14.253	0.000	T statistic > 2 ➔ significant P value < 0.05 ➔ significant The Ka variable plays an important role in influencing K_T.
cv <- K_T_	11,127	0.000	T statistic > 2 ➔ significant P value < 0.05 ➔ significant The Cv variable plays an important role in influencing K_T.

Based on the PLS-SEM analysis results (Fig. 6 and Table 7), the variables that play roles and can explain K_T are C_V, D, Df, and Ka.

3.7. Fit Models

Fit model is a statistical model that demonstrates the extent to which a model is suitable with a series of observations.

✓ Standardized root mean square residual (SMSR) < 0.10 or 0.091: The model will be considered fitted [22]. This evaluation assesses the appropriateness of the observed correlations or relationships.

✓ D-ULS (the squared Euclidean distance) and d-G (the geodesic distance): The values of d-ULS and d-G are not related to any value because the level intervals of d-ULS and d-G (and SRME) are not obtained by performing the procedure of normal bootstrapping.

✓ Chi-square cannot be utilized as the sole test for assessing goodness of fit for the overall model because it is sensitive to sample size. As the sample size increases, so does Chi-square, which can lead to the rejection of the model, even when the difference value between the sample covariant matrix (S) and the model covariant matrix or S(T) is minimal and small.

✓ The normal fit index (NFI) typically yields values ranging from 0 to 1. The closer the value is to 1, the better the fit of the data to the developed model.

Table 8 presents the fit models.

Table 8 Fit models (Own study)

	Saturated Model	**Estimated Model**
SRMR	0.091	0.091
d-ULS	0.124	0.124
d-G	0.311	0.311
Chi-Square	21.850	21.850
NFI	0.725	0.725

4. Conclusions

The evaluation of reservoir storage capacity currently focuses primarily on its ability to provide water supply, but it has not examined its capability to offer flood storage. In addition, the performance assessment of the reservoir storage capacity is not classified as very good, good enough, or not good. The performance of multi-purpose reservoir storage capacity is determined using the PLS-SEM approach. Based on the PLS-SEM analysis results (Fig. 6 and Table 7), the variables that play roles and can explain K_T are C_V, D, Df, and Ka. The outer loading shows that the variable combinations of C_V, D, D_f, and Ka can be used for further modeling. Thus, the influencing variables are discharge variation coefficient (C_V), water demand for utilization (D), reservoir capacity demand for flood storage (Df), and carry-over storage capacity (K_A).

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