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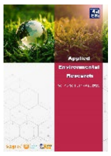

Research Article

Re–operating the Bhumibol and Sirikit Dams Using Hybrid Neuro–Fuzzy Technique to Solve the Water Scarcity and Flooding Problems in the Chao Phraya River Basin

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Abstract

The decision support system to reservoir re–operation using Artificial Intelligence has been broadly studied and proven in term of the operational performances for both single and multiple reservoir system, this study applied Adaptive Neuro Fuzzy Inference System (ANFIS) technique for reservoir re–operation in Chao Phraya River Basin aiming to reduce water scarcity and flooding problems in the central region of Thailand. ANFIS is an integrated approach in which neural networks are utilized to enhance the fuzzy inference system and create fuzzy "IF–Then" reservoir operational guidelines with proper membership functions for reservoir re–operation. In this study, ANFIS operating rules were trained using two different datasets; long–term dataset (scenario 1) and water year–based dataset (scenario 2). It is revealed that the extent of yearly water deficit in critical dry years are totally reduced to nearly zero when re–operating with ANFIS operation rules, except in the year 2012. However, the yearly water deficit in year 2012 is also substantially reduced from 504 MCM by the current operation to 127 and 119 MCM for scenario 1 and scenario 2, respectively when two scenarios of ANFIS–based reservoir re–operation model were performed. Moreover, considerable total amount of spilled water from BB and SK Dams is definitely declined to 0 and 37 MCM in years 2002 and 2011, respectively when water year–based ANFIS model was implemented. In addition, it is expressed that average water storages of two main dams obtained from two scenarios of ANFIS model are substantially increased up to +6.08% and +6.94% for BB Dam and +0.09% and +1.62% for SK Dam in comparison with the current operation. This signifies that supplying water from dams to meet the target water demand through adaptive fuzzy–rules can be well handled and flooded water can be minimized.

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Introduction

The effectiveness of dam and reservoir operation systems has rationally supported the sustainable management of water resources [1]. The issues on adaptive water resources management by altering the reservoir operation policy have been widely addressed due to realization on the adverse impact of climate changes and frequent occurrences of natural disasters in various parts of the world [2–6]. Severe flood and intense and prolonged drought have become an urgent threat to economic development globally [7]. It is stated that water crisis due to flood and drought could be solved effectively with adaptive and integrated reservoir management approach [8]. Consequently, optimal long–term reservoir management through modern Artificial Intelligence (AI) technologies as well as the best operational practice driven by up–to–date reservoir operating policy have been proposed and brought into action to cope fruitfully with natural disasters [9].

Nowadays, dam and reservoir re–operation has been recognized as one of the most excellent approaches to alter the existing operation and management procedures. It can also maintain or maximize the multiple benefits obtained from reservoir operation [10]. Accordingly, the reservoir re–operation techniques have been broadly adopted to achieve sustainable water allocation and reduce flood and drought risks in various parts of the world [11].

In the past few decades, great attention on enhancing benefits of existing dam operation through using operational rule curve has been drawn to provide guidance for decision of dam release. It is renowned that rule curves have been commonly applied for reservoir operation due to its simplicity for dam operators. However, the conventional rule curve has been developed specifically for a single reservoir by disregarding present circumstances of climate and watershed conditions [12]. Controlling releases by rule curves is made based on the established bounds which depend on time of year to maintain reservoir water level. Therefore, achieving the ultimate goal in solving extreme flood and drought problems and operational sustainability of reservoir water by using traditional rule curve have been hardly found.

In recent decades, computer–aided tools using AI technologies have become more popular and advanced in many fields, especially in water resources management and planning system [13]. AI is one of the advanced computer–based techniques for simulating systems with human intellectual abilities [14–15]. In other words, AI can be referred to as the capability of a computer–controlled practice to accomplish tasks that are generally linked to intelligent experiences [16]. In computer science, AI is sometimes termed as Machine Intelligence (MI) when it is demonstrated as intelligence with machines against the natural intelligence exhibited by either humans or other animals. Deep Learning (DL) and Machine Learning (ML) are subspecialties of AI which are very usable techniques particularly for complex decision–making. ML algorithm includes logic programming, decision tree analysis, clustering, reinforcement learning, and Bayesian networks [17]. DL models originated from Artificial Neural Networks (ANN) due to their learning ability from data. Along with the various AI applications, ANN is one of the optimal approaches commonly applied for operational reservoir simulation in many parts of the world [18–19]. It is proven that ANN has been successfully applied for development of the reservoir inflow prediction and reservoir operation simulations by learning from long–term reservoir operation data and a large amount of historical hydrological data [20–21]. After that, some researchers linked the ANN algorithm with other reasoning and optimization algorithms to increase the ANN models' accuracy and investigated using the upgraded ANN algorithm for reservoir strategic planning [22]. For instance, ANN was combined with a genetic algorithm (GA) optimization technique and proved the suitability of the advanced GA–ANN algorithm in reservoir operation systems [23]. For forecasting reservoir inflow, ANN was connected with the evolutionary algorithm and evaluated the performance of a novel Evolutionary–ANN method [24].

In addition to the above two evolutionary ANN algorithms, Adaptive Neuro Fuzzy Inference System (ANFIS) was established as a novel hybrid approach of ANN and Fuzzy Logic System (FLS) in the early 1990s [25]. Many studies have proven that the ANFIS model can create the reservoir operating model more efficiently than the classical fuzzy rule–based model if the informative data is sufficiently provided [26]. Importantly, ANFIS–based reservoir operation model can extract the long–term reservoir operational rules with increased problem–solving and computerized simulation algorithms [27–30].

In this study, ANFIS technique was selected to evaluate the prospective performances of the reservoir re–operation system and analyze its risk compared to the current operation. ANFIS was established to provide operational guidance for re–operation of the Bhumibol (BB) and Sirikit (SK) Dams not only to guarantee flood control safety but also to alleviate water scarcity in the Chao Phraya River Basin (CPYRB).

Consequently, re–operating the BB and SK Dams with ANFIS model through long–term and water–year–based datasets were conducted in this study aiming to minimize the water scarcity and flood problems in the central region of Thailand. This envisages the current water stress which calls attention to the establishment of well–prepared preparatory and action plans for climate change adaptation in the future.

Study area

The BB and SK Dams are large multiple purposes dams constructed across Ping and Nan Rivers, respectively which are two main tributaries contributing flow to the Chao Phraya River as shown in Figure 1. They have been used as the principal water supply source not only to supply water for agricultural and non–agricultural needs but also to prevent hazardous droughts and huge floods predominantly in the Chao Phraya River Basin in the central region of Thailand. BB Dam has been jointly operated with the Sirikit (SK), Khwae Noi Bumrung Dan (KNB) and Pasak Cholasite (PS) Dams by the Electricity Generating Authority of Thailand (EGAT) and Royal Irrigation Department (RID) under the regulatory framework established by the Office of the National Water Resource (ONWR). Operating these multiple dams has been traditionally executed using the static rule curve corresponding to the seasonal and yearly water allocation plan established. It is analyses that more than 70% of water released from dams has been supplied for agricultural water demand in the Greater Chao Phraya Irrigation Scheme (GCPYIS) covering the irrigation service area of 10 million rai along the Chao Phraya, Lower Ping, and Lower Nan Rivers.

The central Thailand has frequently experienced droughts in dry season (Nov.–Apr.) and flooding particularly at the end of wet season (May–Oct.) due to tropical monsoon rainfall. This has created huge economic losses for the country due to impact of flood and drought occurrences. It is reported that floods and droughts have been common natural disasters in CPYRB over the decades [31]. In 2011 and 2021, this region suffered substantial economic and agricultural losses caused by the huge floods that devastated vast areas in the region. In the meantime, some irrigation areas in CPYRB struggled with water deficits for a few consecutive years from 2018 to 2020 leading to a substantial decrease in crop yield production. Since floods and droughts have frequently occurred in this region, the weaknesses of existing operations of these major reservoirs were reported and intensively analyzed to draw a lesson [32].

Materials and methods

1) Data collection

The requirement of vital data for this study includes reservoir water balance–based data, water demand data, and hydrological data in CPYRB. These required data were collected from two main offices; (1) Royal Irrigation Department (RID) and (2) Electricity Generating Authority of Thailand (EGAT). To create the reservoir re–operation model applying the water balance–based approach, the daily reservoir data including reservoir inflow, initial water storage, evaporation losses, and water released from BB and SK Dams were gathered from 2000 to 2020. The total water released from BB and SK Dams were considered as the primary water supply sources to satisfy the water demand in CPYRB. To describe the downstream flow conditions for reservoir operation, the downstream water discharge from the Khwae Noi Bumrung Dan (KNB) Dam was collected at gauged station N.22A on the Khwae Noi River to potentially supply the water demand in CPYRB. In this study, the potential downstream side flow was only considered about 25% of the downstream water discharge from KNB Dam to supply for the water demand in CPYRB. Therefore, 25% of total water demand can be partially satisfied by the potential side flow and the remaining will be supplied by BB and SK Dams. Therefore, some amount of water can be saved and stored in reservoirs for later use in the subsequent dry season period. The target water demand in CPYRB was generated over the same time period in association with the monthly water allocation plans established by RID and EGAT from 2000 and 2020. Water supplied to the target demand nodes was shared by BB and SK Dams in the proportion of 0.44:0.56 which was analyzed from the historical long–term record of dam releases [33].

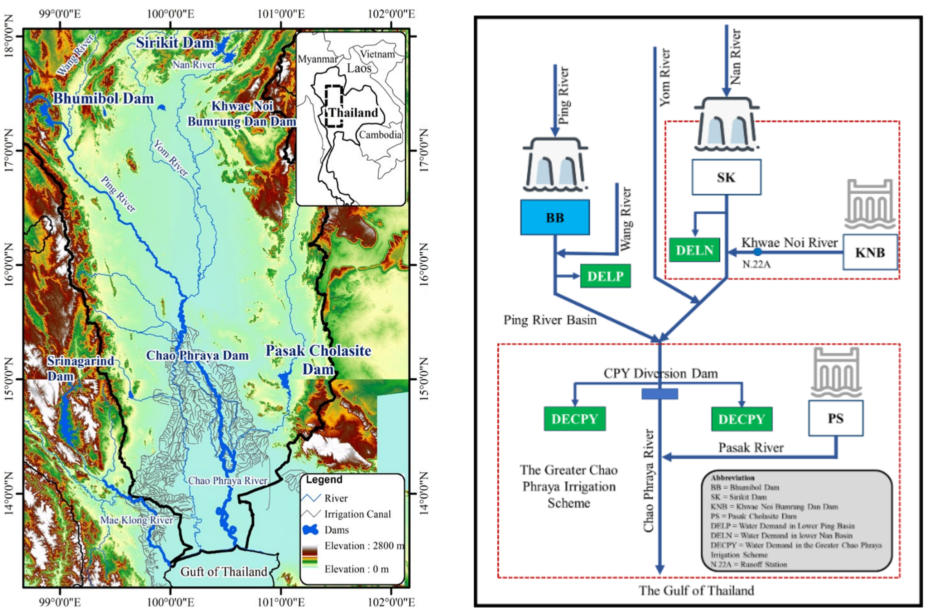

Figure 1 Map of study area and river schematic diagram in the Chao Phraya River Basin.

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To collect and interpret long–term reservoir data, statistical analysis was examined to uncover patterns and trends. For an assessment of climate variability of CPYRB, classification of wet, normal, and dry years based on volume of yearly reservoir inflow from 2000 to 2020 was conducted as shown in Figure 2. The long–term yearly reservoir inflows of BB and SK Dams were evaluated using normal probability distribution function which is considered as the best fitting model. The period in which yearly total inflow is more than 80% probability of normal distribution is considered as wet year. In contrast, period with yearly inflow less than 20% probability of normal distribution is regarded as dry year. In addition, periods with yearly inflow lying between 20% and 80% probability of normal distribution is considered as normal year.

In this study, ANFIS–based reservoir re–operating rules were developed through two scenarios by changing the input dataset of the ANFIS variables.

Scenario 1 (ANFIS–LT): ANFIS "IF–Then" reservoir re–operating rules were developed by using the continuous long–term reservoir data from 2000 to 2020. Therefore, this scenario can be said that the ANFIS re–operating rules were created by only considering the inflow and outflow relationship of the current reservoir operating system. This can get one set of ANFIS "IF–Then" reservoir re–operating rules for the entire simulation time periods.

Scenario 2 (ANFIS–WY): ANFIS "IF–Then" reservoir re–operating rules were developed using the water–year–based dataset which were classified based on the variability of yearly reservoir inflow from 2000 to 2020. Therefore, ANFIS operating rules with water–year–based dataset was separately created for a specific water year, namely, wet year, dry year, and normal year. This can get three sets of ANFIS "IF–Then" reservoir re–operating rules varying with wet year, dry year, and normal year.

2) Development of ANFIS–based reservoir re–operation model

The hybrid neuro–fuzzy–based reservoir re–operation model was developed by aiming to assist the reservoir operating system of BB and SK Dams in CPYRB. The optimal reservoir re–operation rules were solved to accomplish these research goals in terms of water scarcity alleviation and flood moderation by two reservoirs using the Adaptive Neuro–Fuzzy Inference System (ANFIS). The ANFIS–based reservoir re–operation rules were then applied to the water balance–based reservoir operation model developed by MATLAB R2020a version Simulink Toolbox to re–operate the long–term reservoir operation of BB and SK Dams. In addition, the maximum and minimum water releases constrained by the dam and reservoir systems in CPYRB were also assigned in the model as expressed in Table 1. The operational analysis regarding water supply, potential in increasing the reservoir storages, and the amount of spilled water released from the reservoirs was evaluated and also compared with the current operation.

ANFIS is a novel hybrid approach of ANN and Fuzzy Logic System (FLS), which was developed based on the Takagi–Sugeno fuzzy inference system [34]. It is a multi–layer feedforward backpropagation neural network (FFBNN) that can generate a set of fuzzy "IF–Then" rules by identifying the input and output training dataset with appropriate membership functions through a hybrid learning rule. It is also the dissimilarity and advanced learning technique apart from the concept of the conventional fuzzy rule–based model [35]. Through the capability of merging the learning ability to a deep neural network with the transparent linguistic representation of FLS, the ANFIS technique was applied as a powerful tool to ensure more efficient operation of the reservoir system than the classical model based on a rule curve if the informative data was sufficiently provided [36]. Once data entry in the ANFIS model is completed, it could be run for daily simulation and report the daily water release rules as the output result. Therefore, optimal reservoir water release operational rules for BB and SK Dams were generated by ANFIS technique using the MATLAB's Neuro–Fuzzy Designer Toolbox. The flow chart of the modelling process is shown in Figure 3.

To set up the ANFIS structures for this study, three main variables, namely reservoir inflow, reservoir water storage, and target water demand, were determined as input variables. The current dam release was specified as the output variable for the ANFIS model of BB and SK Dams. 80% of the dataset was used for model training to establish the ANFIS rules, and 20% of the dataset was used for model testing to verify the model performances [37]. By doing this, the optimal reservoir operational rules of BB and SK Dams were solved as shown in Table 1.

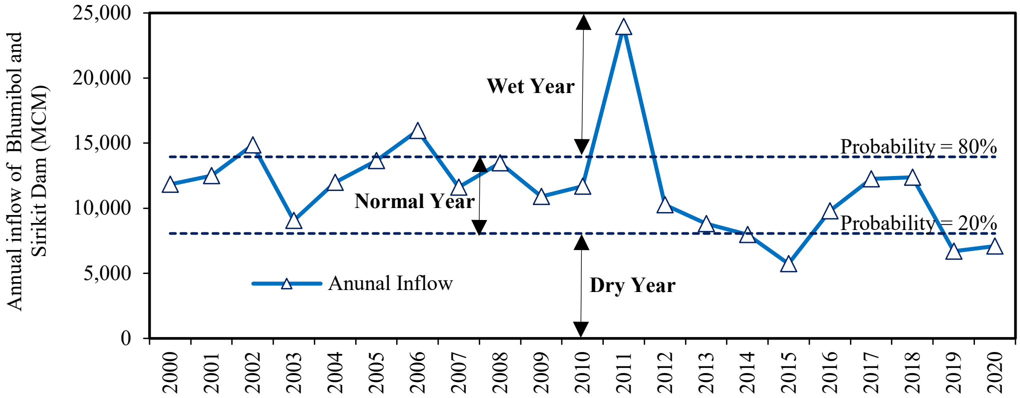

Figure 2 Normal, wet, and dry years classified in the Chao Phraya River Basin.

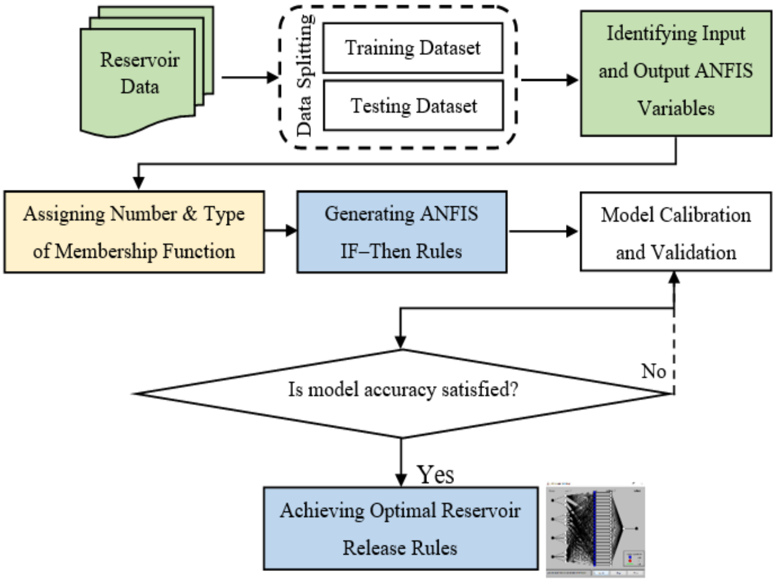

Figure 3 Flow diagram of ANFIS–based reservoir re–operation model of the Bhumibol and Sirikit Dams.

Table 1 ANFIS–based reservoir re–operation model of the Bhumibol and Sirikit Dams

Fuzzification stage	Model setting	Number and type of MF with labelling
Input variables (MCM)		
Reservoir water storage	✓	Three numbers with trapezoidal MF labelling into Low, Medium, and High.
Reservoir inflow	✓	
Target water demand	✓	
Output variables (MCM)		
Reservoir water release	✓	Constant
Fuzzy inference processing stage	Takagi–Sugeno method	
Defuzzification stage	Weighted mean principle	
Network type	Feedforward backpropagation	
Logical operations	AND	
Training epochs set	1,000	
Training error tolerance	Zero	
Model constraints	**BB**	**SK**
Minimum daily water release (MCM)	2.50	3.00
Maximum daily water release (MCM)	69.76	63.24
Minimum water storage (MCM)	3,800	2,850
Maximum water storage (MCM)	13,462	9,510

There are three stages of the controller process in the architecture of ANFIS, namely fuzzification stage, fuzzy inference processing stage, and output defuzzification stage [38], as shown in Figure 4. ANFIS tool is embedded now in MATLAB, therefore, users have to type the command "anfisedit" in the MATLAB's command window to use this valuable tool called MATLAB's Neural Fuzzy Designer Toolbox.

The fuzzification stage is the process of changing the real scalar inputs called fuzzy variables to transform the input data of FLS (fuzzy form) based on the observed information values. It involves two processes; (1) Membership Function (MF) and (2) Labels [39]. The number and type of MF are incredibly varied with the fuzzy input and output data [40]. The various types of MF are triangular MF, trapezoidal MF, Gussion MF, Generalized Bell MF, and so on [41]. And then, labels of FLS can be modified based on either fuzzy variables or expert operation concepts. In this study, the input fuzzy MF was identified into three numbers with trapezoidal type, labelling with low, medium, and high to resemble the existing operation of BB and SK Reservoirs. The output fuzzy MF was identified as a constant membership function. After assigning the membership functions of the fuzzy variables using MATLAB's Neural Fuzzy Designer Toolbox, the fuzzification stage was automatically generated. MF with the smallest range of input fuzzy variable was labelled as "Low" among the three trapezoidal MF. MF with medium range was labelled into "Medium" and the highest range was labelled into "High".

In the fuzzy inference processing stage, the input signals may be involved in one or more variable conditions. This is based on a conditional operation pattern like the "If something occurs, and then something will happen" operator. For instance, whether it is involved in the combination concept of two fuzzy sunsets, then MF will be maximum digit calculating based on mathematical rules. There are two standard inference methods, (1) Mamdani's fuzzy inference method and (2) Takagi Sugeno's fuzzy inference method. ANFIS is based on the Takagi–Sugeno fuzzy inference method, which is closer to human brain thinking than conventional Mamdani's fuzzy inference logical systems.

After assigning the fuzzy variables along with the membership function, the defuzzification stage is expressed as the output variable resulting from ANFIS. There are three categories of defining the output defuzzification progression; (1) centroid principle, (2) maximum membership principle, and (3) weighted mean principle. In this study, weighted mean principle which is one of the simplest and widely used defuzzification technique with high accuracy, was selected for output defuzzification of ANFIS model to calculate the mean values for the input variables according to their related membership function. The ANFIS–based reservoir release rules were derived after the number of training epochs of 1,000 was reached. Zero error tolerance was set in the model through a hybrid learning rule combining the backpropagation gradient descent and a least squares method. After that, the statistical performance metrics were evaluated to assess the ANFIS–based reservoir re–operation performances for both model calibration and validation. Finally, optimal reservoir operational rules of BB and SK Dams were generated. There were 27 "IF–Then" optimal reservoir operational rules for both long–term and water–year–based dataset scenarios performed by ANFIS technique.

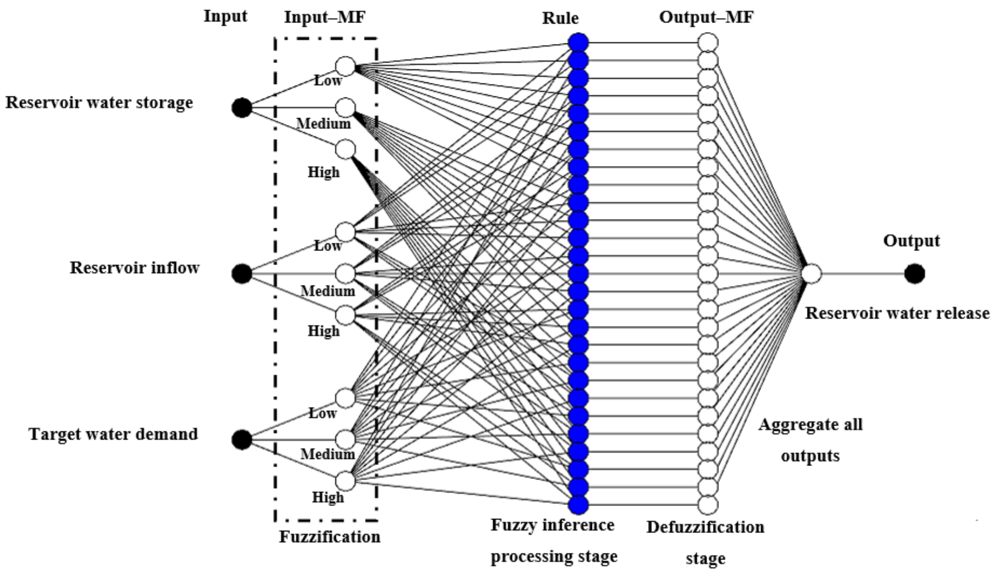

Figure 4 ANFIS structure for reservoir re–operation of the Bhumibol and Sirikit Dams.

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Results and discussions

1) Performance assessment of model calibration and validation of the ANFIS–based reservoir re–operation model

To evaluate the performance of the model calibration and validation obtained from ANFIS model, the statistical parameters, namely, Correlation Coefficient (R), Coefficient of Determination (R^2), Mean Squared Error (MSE), and Root Mean Square Error (RMSE) were used to measure correlation between observed and simulated releases of two main dams. The statistical performances for the training dataset (2000–2015) and testing dataset (2016–2020) accomplished by ANFIS model is presented in Table 2. It is found that the training performances of BB and SK Dams reach highest with R values of 0.84 for scenario 1, and 0.85 for scenario 2, respectively. Similarly, the statistical training performances measured in terms of R^2 of BB and SK Dams are equal to 0.70 for scenario 1. The values of R^2 for BB and SK Dams are between 0.70–0.72 for scenario 2 when the water year–based dataset was trained by ANFIS model. It is also revealed that testing performances for two scenarios done by ANFIS model are slightly decreased than those performances evaluated using training data. However, R and R^2 values lie above 0.76 and 0.57, respectively, which can be considered as strong correlation. Moreover, the smaller values of MSE and RMSE for both the model training and testing are found for both scenarios indicating that model fits the observed data well. This can be concluded that ANFIS model can establish reasonable operation rules representing existing operation of BB and SK Dams as it can provide strong correlation between observed and simulated water releases by ANFIS rules.

2) Daily dam releases and water storages accomplished by the ANFIS–based reservoir re–operation model

As previously mentioned, to achieve the ultimate purpose of reducing the water scarcity and flooding problems in the basin, two scenarios of reservoir re–operation models of BB and SK Dams in CPYRB were established through the long–term and water year–based ANFIS operating rules. The comparative results of daily reservoir releases accomplished by the ANFIS model are compared to the current operation from 2000 to 2020 as graphically shown in Figure 5. It is exhibited that the release patterns obtained from both scenarios of ANFIS–based reservoir re–operation model conform well with the current releases of BB and SK Dams. The reservoir water storages performed by long–term–based ANFIS rules is likely close to the current operation. However, it is slightly lower than that obtained by water year–based ANFIS rules in the initial period from 2000 to 2008 and considerably higher in the period from 2009 to 2012. The water storages for both scenarios are gradually increased since 2009 and reached the highest in 2011. After 2012, the reservoir storages for both scenarios are marginally lowered. This is because of the variability of reservoir inflows after 2012, which are much lower than the average long–term record as illustrated in Figure 6.

3) Assessment of water scarcity accomplished by the ANFIS–based reservoir re–operation model

To assess the severity of water scarcity as a result of reservoir re–operation, the daily Total Water Supply (TWS) by two scenarios were computed and compared with the Target Water Demand (TWD). In this study, TWS was defined as the combination of water released from BB and SK Dams and potential downstream side flow. The coefficient of determination (R^2) was used to describe how much TWD closely matches TWS which was accomplished by ANFIS model. The comparative results are illustrated in Figure 7. For the current operation, R^2 value is 0.7288, indicating that TWS is 72.88% linearly related to TWD. However, when ANFIS re–operation models were applied, the R^2 values for both scenarios are considerably increased above the desirable range of 0.8373 and 0.9226 for scenario 1 and scenario 2, respectively which are higher than current operation. This indicates that supplying potential water to meet TWD by ANFIS models can be well handled to alleviate water scarcity in the basin.

Table 2 Statistical performance measurement for model calibration and validation of the ANFIS–based reservoir re–operation model

Statistical performances	BB Dam				SK Dam			
	R	R^2	MSE	RMSE	R	R^2	MSE	RMSE
Model training (80% of the total simulation time steps)								
S1: ANFIS–LT	0.84	0.70	42.60	6.53	0.84	0.70	45.54	6.75
S2: ANFIS–WY	0.85	0.72	39.91	6.32	0.84	0.70	47.07	6.86
Model testing (20% of the total simulation time steps)								
S1: ANFIS–LT	0.76	0.57	29.52	5.43	0.76	0.57	29.28	5.41
S2: ANFIS–WY	0.81	0.65	22.34	4.73	0.76	0.57	29.24	5.40

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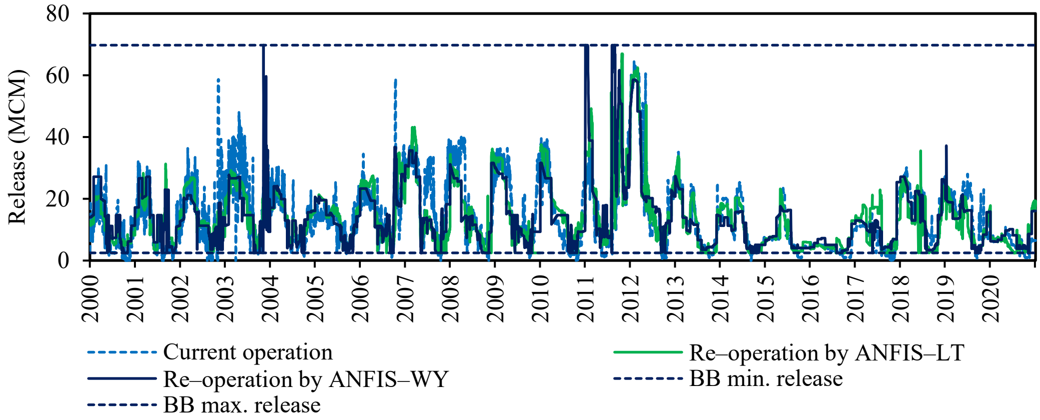
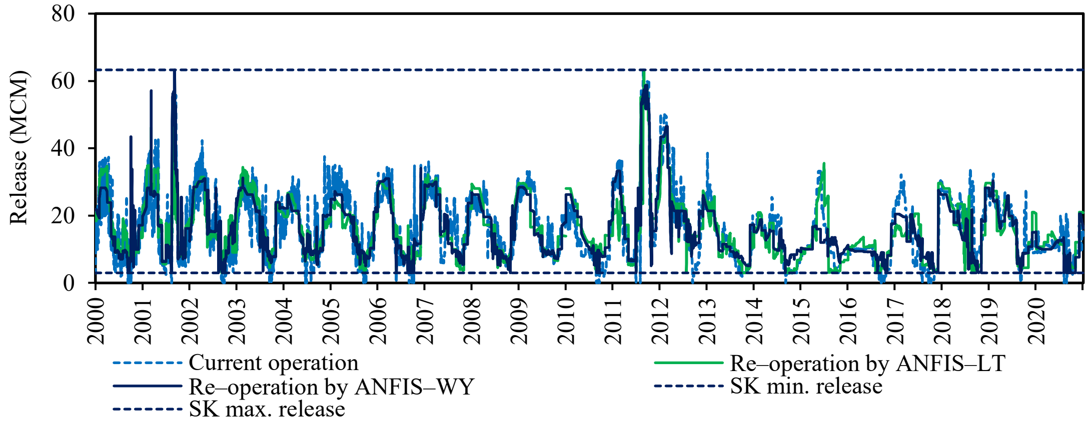
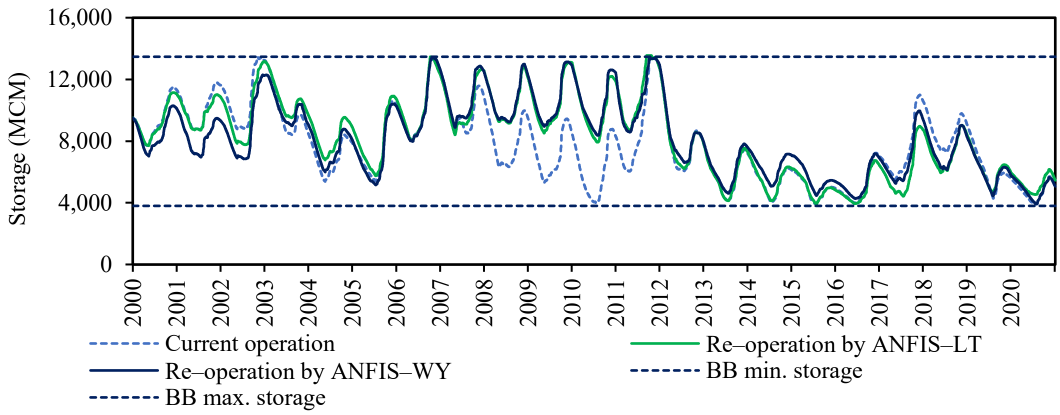


(a) BB Dam

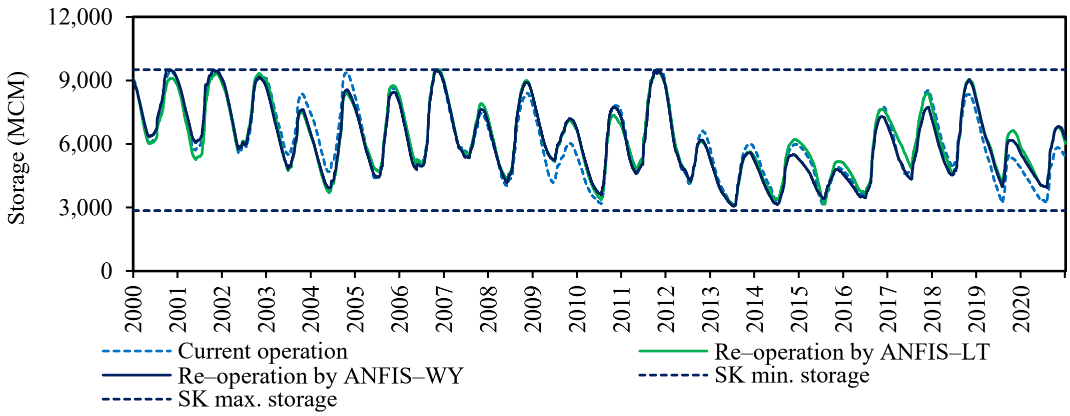


(b) SK Dam

Figure 5 Daily reservoir releases accomplished by the ANFIS model.



(a) BB Dam



(b) SK Dam

Figure 6 Daily reservoir water storages accomplished by the ANFIS model.

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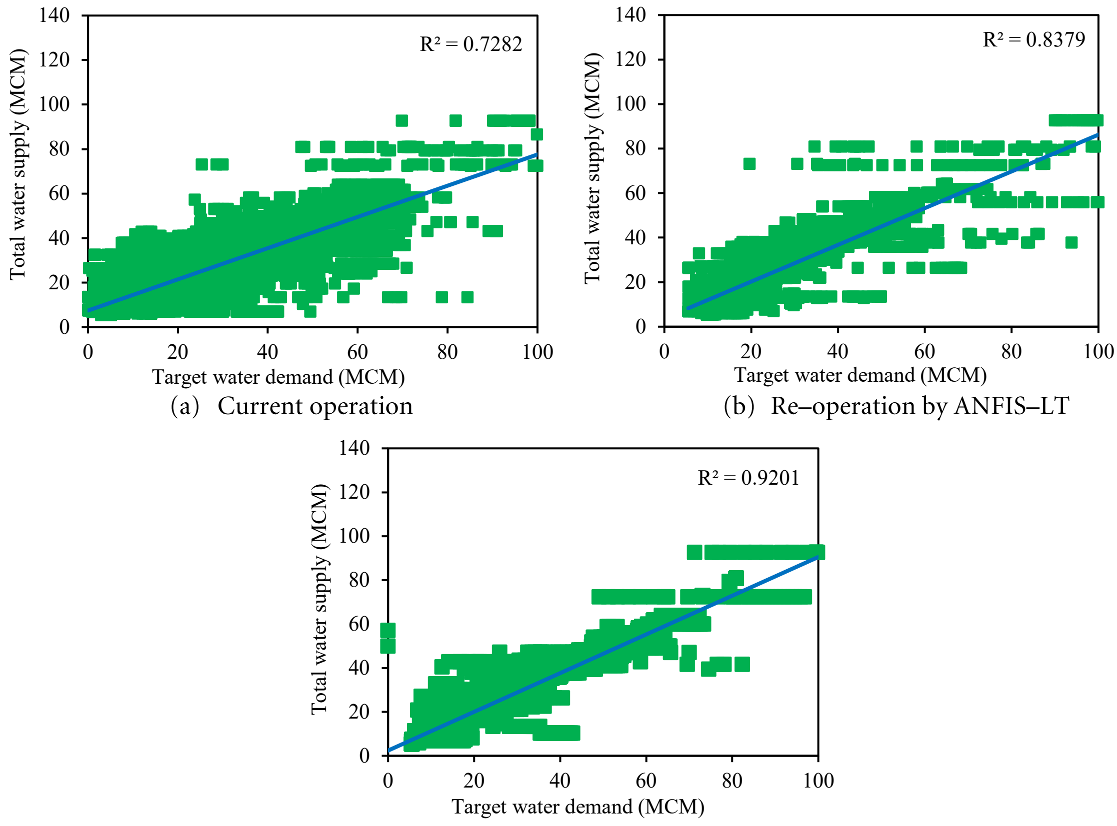

(a) Current operation (b) Re–operation by ANFIS–LT

(c) Re–operation by ANFIS–WY

Figure 7 Correlation between target water demand and total water supply by ANFIS model.

In this study, the water deficit is considered non-existent when TWD is fully met by TWS. Meanwhile, the amount of water deficit is quantified when the TWS is less than TWD. It is illustrated from the results that the water deficit for the current operation is occurred in the critically dry years in 2010, 2012, 2016, 2017, and 2020 which amounts to 1,480, 504, 410, 918, and 22 MCM, respectively. This is because the inflows into BB and SK reservoirs are predominantly low during the critical dry years, but water demand is anticipated to rise intensely. However, when two scenarios of the ANFIS–based reservoir re–operation model were performed, the extent of yearly water deficit in these critical dry years are substantially reduced to 0–127 and 0–119 MCM for scenario 1 and scenario 2, respectively as can be seen in Figure 8. It is reflected that the ANFIS–based reservoir re–operation models seek to ascertain the amount of water to be released to satisfy the target water demand at all reasonable time steps. They use a series of fuzzy if–then rules developed based on current reservoir operation to determine the amount of dam release at each time step. In addition, the water year–based ANFIS rules can perform well in reducing the extent of water deficit volume particularly in the critical dry years, which is better than those applied by long–term–based ANFIS rules. This is due to the fact that the water year–based ANFIS rules were generated corresponding to historical reservoir management practice to extreme drought events. Therefore, magnitude of water deficit during drawdown periods of reservoirs performed by water year–based ANFIS rules is smaller than those obtained by ANFIS rules established using long–term dataset.

4) Potential for increasing water storages by the ANFIS–based reservoir re–operation model

The potential for increasing water storages of BB and SK Dams was investigated to describe capacity in supplying water over the dry season and coping with water deficit for the next coming years by the ANFIS–based re–operation model. The comparative results of average yearly water storages of two main dams are summarized in Table 3. As the average yearly amount of reservoir water released from 2000 to 2020 by the ANFIS–based reservoir re–operation models are definitely lower than the current operation by –1.67% and –0.22% for scenario 1 and scenario 2, respectively, this leads to a substantial increase in reservoir storages of BB and SK Dams. In comparison to current operation, the water storages of BB and SK Dams accomplished by the ANFIS model are increased up to +6.94% and +1.62%, respectively for scenario 1, and +6.08% and +0.09%, respectively for scenario 2. For the seasonal analysis, it is revealed that the potential for increasing water storages of BB and SK Dams in wet season is continually higher than in dry season for both scenarios. This is because the considerable amount of dam releases in the rainy season from BB and SK Dams delivered to the target demand points in CPYRB are reduced due to potential downstream flow conditions and local rainfall. Consequently, some amount of savable water can be stored in reservoirs before the dry season starts. This envisages that ensuring efficient and equitable water supplies to the water demand sectors by dam–reservoir system can be well operated to moderate the extent of water scarcity especially in El Nino episodes.

5) Assessment of reservoir spilled water accomplished by the ANFIS–based reservoir re–operation model

In the reservoir operation system, the spillway structure is controlled to discard the surplus water from a reservoir after filling up to its maximum capacity. The Maximum High–Water Level (MHWL) is a design level to maintain the maximum reservoir storage; therefore, the water above MHWL is overflowed as the spilled water and discharged into downstream river. In this manner, hydroelectric power cannot be potentially produced. Moreover, it reflects the sign of flooding downstream when the amount of spilled water exceeds the river capacity. Figure 9 shows volume of spilled water in the historical wet years when re–operating with the ANFIS operation rules through long–term and water–year–based datasets. It is illustrated that the ANFIS–based reservoir re–operation model can considerably lower the amount of spilled water from BB and SK Dams compared to the current operation. The yearly volume of spilled water from BB Dam for the current operation is found to be 195 and 342 MCM which are occurred during the late rainy season in extreme flood years 2002 and 2011, respectively. By re–operating with the ANFIS–based reservoir re–operation model, non–spilled water from BB Dam is definitely existed in 2002 for both scenarios. In addition, yearly volume of spilled water of BB Dam can be radically reduced to 94 and 32 MCM by scenario 1 and scenario 2, respectively. Similarly, releasing water of SK Dam through the controlled spillway is found in the 2011 Thailand Flood with the total spilled water of 184 MCM. By re–operating with the ANFIS–based reservoir re–operation model, volume of spilled water of SK Dam can be reduced to 14 and 5 MCM by scenario 1 and scenario 2, respectively. This signifies that the extent of spilled water occurred in the lower CPYRB as a result of dam–reservoir re–operation by the ANFIS model can be reduced. As ANFIS operation rules of scenario 2 were generated from water year–based datasets, this means that determining specific reservoir release rules in dry, normal and wet years is made based on their distinct hydrological conditions and operational characteristics. Therefore, water year–based ANFIS rules specifies higher amount of reservoir release than the long–term–based ANFIS rules during the refilled periods. Consequently, the available water storage in reservoirs can be depleted leading to the reduction of spilled water in severe flood events.

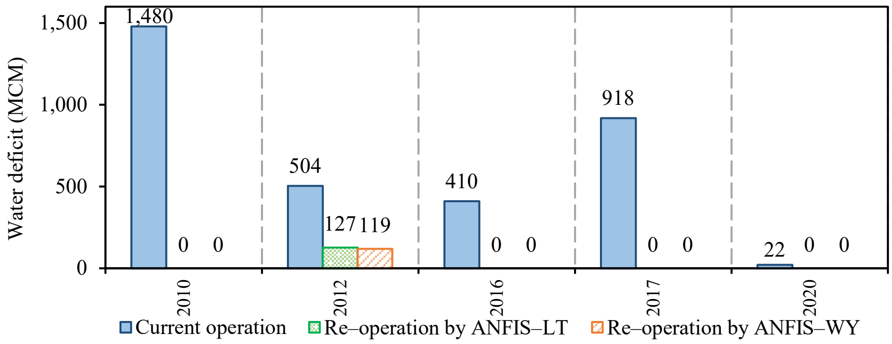

Figure 8 Yearly water deficit in the historical dry years when re–operating with the ANFIS operation rules through long–term and water–year–based datasets.

Table 3 Potential of increasing reservoir water storage accomplished by ANFIS model

Scenario	BB Dam			SK Dam		
	DS	WS	Yearly	DS	WS	Yearly
			Avg. water release (MCM)			
Current operation	3,424	1,780	5,203	3,687	2,285	5,972
S1: ANFIS–LT	3,283	1,786	5,069	3,623	2,296	5,919
S2: ANFIS–WY	3,280	1,923	5,203	3,585	2,362	5,948
			Increased water storage (Δ%)			
Current operation	–	–	–	–	–	–
S1: ANFIS–LT	+5.98	+8.08	+6.94	+1.17	+2.14	+1.62
S2: ANFIS–WY	+5.22	+7.09	+6.08	–0.88	+1.21	+0.09

Remark: Δ is the different values compared to the current operation, DS is dry season, and WS is wet season

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Conclusions

Re–operating the Bhumibol and Sirikit Dams with Adaptive Neuro–Fuzzy Inference System (ANFIS) approaches as well as modelling exercises to generate the series of reservoir operational release rules were conducted in this study. The ANFIS–based reservoir re–operation modelling is a state–of–the–art technology and self–learning approach between the input and output linguistic variables that resembles the current operation in controlling complex reservoir operating systems. The main finding of this study indicates that, in comparison to the current operation, changing the operating policy for reservoir re–operation with ANFIS can help reduce water scarcity and flooded water in extreme weather events. It is also assured that re–operating with ANFIS model can help stabilize the water availability from BB and SK Dams, particularly at the end of wet season when the reservoir water storage is substantially increased. This indicates a higher possibility in satisfying the water requirements during dry season in this region. In addition, ANFIS can help envisage more transparent operating rules by extracting the release features of the system from the historical dataset representing extreme weather and climate events and tendency in water demand patterns. This enables the dam operators to make a wide range of decisions based on certain release rules to moderate operational risk in this region. However, certain limitation of ANFIS model for reservoir operation is that high computerized time is spent with larger input variables. In addition, setting up the input and output structures of ANFIS model for multi–reservoir operation is made based on the systemic concept of single reservoir system to separately train the ANFIS model for each dam. Moreover, to extract specific operational rules during critical events and to reduce loss of interpretability using long–term dataset, water year–based ANFIS model is highly recommended for flood and drought mitigation.

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