Applied Water Science (2026) 16:135
https://doi.org/10.1007/s13201-026-02820-2

ORIGINAL ARTICLE

Multiple reservoir optimization using constraint programming for water scarcity resilience in the Chao Phraya River Basin

Wudhichart Sawangphol[1] · Areeya Rittima[2] · Yutthana Phankamolsil[3] · Jidapa Kraisangka[1] · Allan Sriratana Tabucanon[4] · Yutthana Talaluxmana[5] · Varawoot Vudhivanich[6]

Received: 8 June 2025 / Accepted: 4 March 2026

Abstract

Reservoir optimization has gained increasing attention as a cornerstone of sustainable development and water resource resilience, particularly in regions prone to climate extremes. To address these challenges, this study introduces a novel Constraint Programming (CP) for multiple reservoir optimization to enhance water scarcity resilience in the Chao Phraya River Basin (CPYRB). CP models with and without incorporating travel time taken from dams to water demand nodes, CPM1 and CPM2, were accordingly formulated to find optimum daily release schemes of major dams in the basin. The development of the CP models in CPYRB utilized Python's GEKKO library with the IPOPT solver, which offers a user–friendly modeling environment for large–scale, nonlinear, and constrained optimization problems. The simulated results from 2000 to 2020 demonstrated that CPM1 and CPM2 models could generate different daily release schemes to recommend a release guideline trajectory, while average annual releases accomplished by CP models could closely replicate current operation. Moreover, both models could increase the end–of–wet–season storage in the reservoir system by 2,712 and 1,265 MCM/yr, respectively, to potentially supply overplanting during the dry season, revealing improved water scarcity resilience in the basin. By incorporating travel times between releases from different dams and the various demand nodes, CPM2 offered more realistic and effective operations to timely and spatially distribute water in the irrigation farm area than CPM1. This ensured that water was supplied at various water distribution zones at the right time of use while satisfying system–wide objectives and time–dependent constraints. Importantly, the CPM2 model, which exhibited the smallest discrepancy in average total releases from the Bhumibol and Sirikit Dams, demonstrated a strong long–term quantitative agreement with the current operation. Moreover, the CPM1 model demonstrated a significant advantage over other optimization models including deep reinforcement learning, non–linear programming, and adaptive neuro fuzzy inference system in view of increasing the long–term end–of–wet season storage levels of two main storage dams, achieving + 15.73% and + 16.36% for Bhumibol and Sirikit Dams, respectively. This proposed CP framework provides a robust operational tool for dam operators to enhance water scarcity resilience in complex, highly constrained multi–reservoir systems.

Keywords Constraint Programming · Water Resilience · Multiple Reservoir Optimization · Chao Praya River Basin

Introduction

The growing concern regarding the imbalance between water availability and water demand has addressed the significant role of reservoir optimization for water resource planning and management (Feng et al. 2020; Niu et al. 2021). The importance of reservoir optimization for sustainable development has been broadly recognized by decision makers, especially in regions where limited and excessive water resources usually exist. The concept of optimization is basically positioned between the two extremities of deficiency and excess (Sinha and Purwar 2024). This optimization approach has been widely employed to resolve the competing objectives across multiple multipurpose reservoirs,

Communicated by Peiyue Li.

Extended author information available on the last page of the article

Published online: 31 March 2026

especially given concerns about climate variability and growing water demand.

Various traditional optimization techniques including Linear Programming (LP) (Senlin et al. 2017; Zetai et al. 2022), Non–Linear Programming (NLP) (Unver and Mays 1990; Kyaw et al. 2024), and Dynamic Programming (DP) (Yakowitz 2014; Cervellera et al. 2015; Giuliani et al. 2021; Ayele et al. 2022), etc. have been developed and widely applied over the past few decades to address the reservoir release scheduling problems (He et al. 2024). However, each of these optimization techniques has significant limitations. As the assumption of LP is based on the linear relationships for both the objective function and constraints restricted in the model, consequently, it struggles to represent the non–linearity that exists in real–world problems. While NLP offers considerable advantages in its capability, its low convergence speed and high computational demands has emerged as significant challenges for practical applications (William 1985; Bai et al. 2015). DP faces the challenges of curse of dimensionality, indicating the resource requirement and computational complexity particularly for large scale problems (Li et al. 2020; Liu 2021). In addition, Stochastic Dynamic Programming (SDP), a specific form of DP designed to deal with problems involving the presence of uncertainty and stochastic nature, has several limitations. The curse of dimensionality restricts the dimension of the reservoir system with two or three reservoirs for SDP applications due to a large number of state variables (Giuliani et al. 2021). The curse of modelling contributes the additional state variables (Tsitsiklis and Van Roy 1996). Moreover, the curse of multi–objectives limits the number of objective functions of the SDP model (Giuliani et al. 2014, 2021).

To leverage global search capability and model simplifications for the small to large–scale reservoir optimizations under the emerging climate challenges, numerous optimization algorithms inspired by natural evolution have been intensively developed, such as Genetic Algorithm (GA), Heuristic Algorithm (HA), and Particle Swarm Optimization (PSO). The optimized reservoir release was achieved using the GA algorithm to balance the competing interests among hydropower production, flood control, irrigation, and environmental needs (Wahyuni et al. 2024). The capability of GA for reservoir optimization was also demonstrated in view of the reduction of water deficit when high uncertainty of long–term reservoir inflow was addressed (Mezenner et al. 2024). Optimal operation of multiple reservoir systems was obtained using Simulated Annealing (SA), a probabilistic metaheuristic algorithm. The problem representation and parameter selection were exhibited and SA's ability to replicate the global optimum solution was examined and compared to LP (Teegavarapu and Simonovic 2002). Metaheuristic Algorithm (MHA) was used to trade–off between water supply and flood control mitigation for optimal reservoir operation (Lai et al. 2023). In addition, the comparative studies among PSO, GA, and swarm–based algorithms were conducted to investigate the validity and robustness of model performances for multi–objective and multi–reservoir optimizations (Chen et al. 2020) and reservoir hydropower optimization (Akbarifard et al. 2020).

In addition, fuzzy optimization combining traditional optimization techniques with fuzzy logic approach to describe vagueness and ambiguity of key relevant variables in term of fuzzy set, has been considerably employed for reservoir operation (Shrestha et al. 1996; Faris et al. 2021; Pawar et al. 2023; Yutthana et al. 2024). Fuzzy linear programming was applied for the multi–reservoir optimization to improve decision–making under climate variability conditions (Choudhari and Raj 2023). It is shown that implementing the multiple–constrained problems in a complex reservoir system using these conventional optimization techniques is often inappropriate and computation time–consuming (He et al. 2024).

Constraint Programming (CP) is a problem–solving technique rooted in Artificial Intelligence (AI), computer science, and operation research (Hentenryck and Hoeve 2023; Hentenryck 2024). It generally studies the computational system based on variable constraints in solving complex problems (Leite et al. 2014). CP has been proven as a powerful tool for modelling and solving a broad range of Constraint Satisfaction Problems (CSPs) and Constraint Optimization Problems (COPs), including resource scheduling and planning, configuration, vehicle routing, bioinformatics, and combinatorial optimization (Rossi et al. 2006). In operation research, CP is an emergent field prioritizing the feasibility of finding solution rather than optimization to find optimum solution. It focuses on the constraints and variable domains over the explicit objective function (Dabas and Cooner 2014). It offers significant advantages in these areas by supporting fast program development, large neighborhood search with complicated variables, economic program maintenance, and effective runtime performance. The representation of CP problems is directly simplified by constraints, resulting in simple and adaptable programs to the changing requirements (Wallace 1995). Performance of CP modelling is substantially influenced by key factors, including constraint complexity, search sample size, and constraint propagation.

Modelling CP fundamentally begins with identifying relevant variables, variable domains, and constraints to define the problems. Variables and their associated domains are identified to characterize the unknowns in a specific problem. The power of CP relies on the constraints, which can be expressed as both logical relations or arithmetic equations to restrict the possible values of variables within their domains.

The core concept of the CP model is to find the feasible solutions of the given problems that satisfy all constraints. Constraint propagation, intelligent backtracking, and search space exploration are fundamental interconnected elements of problem–solving approach for constraint programming (Bessiere 2006; Freuder and Mackworth 2006). Constraint propagation, is used to actively reduce variable domains or search space which cannot participate in the solutions (Barták 2001). Intelligent backtracking avoids redundant search, while search space exploration guides the overall search process for the given problems. Finally, the CP solver then leverages these reduced variable domains in its search algorithm to effectively find solutions. In general, Constraint Optimization Problems (COPs) which is a generalization of CSPs incorporating objective functions in addition to the variables and constraints, can be modelled and solved by CP solver. Furthermore, CP modelling can be applied to Multi–Objective Optimization Problems (MOCPs), which involve multiple objective functions, to find sets of optimal solutions. The classical constraint solvers are ILOG Cplex CP Optimizer, ECLiPSe, and SICStus Prolog (Rossi et al. 2006). In this study, the GEKKO optimization suite (Beal et al. 2018) has been used as a tool for modeling and finding optimization solutions. GEKKO is known as a high–level object–oriented Python package that develops constraint models and finds an optimal solution for them. The nature of GEKKO is solver–independent, allowing the models to be solved by various constraint solvers.

In the context of reservoir operation, certain capabilities are particularly important because decision variables are heavily constrained by physical processes and operational regulations. Factors such as reservoir mass balance relationships, storage limits, flood threshold levels, ecological minimum flow requirements, and hydropower operating constraints can all be framed as limitations. These constraints collectively restrict the feasible combinations of storage and release decisions. By implementing constraint propagation, infeasible combinations that would violate any of these conditions can be systematically eliminated early in the solution process. This approach leaves only release trajectories that align with all physical and policy requirements of the system. The ability to integrate a comprehensive set of constraints with efficient searching is a significant advantage of CP in the management of complex water resource systems.

Compared to DP, solution strategy for CP is based on eliminating invalid solutions through constraint propagation. On the other hand, DP breaks problems into overlapping subproblems and builds solutions incrementally. Consequently, number of subproblems, degree of overlapping, and memory requirement are key factors influencing the DP performance. Moreover, adding or removing constraints by CP is more flexible than DP. Although CP offers the considerable potential benefits, its application and critical review in the context of reservoir optimization and water resource allocation, has been limited compared to DP. Adoption of CP for reservoir release scheduling was considerably investigated for single reservoir at the Bhumibol dam in Thailand to minimize water scarcity and excessive dam release (Sawangphol et al. 2024). The model was formulated using MiniZinc, a well–known high–level declarative modelling language, designed as a standard language for constraint programming to describe and tackle the optimization problems (Nethercote et al. 2007). It was then solved using Interior Point Optimizer, IPOPT, an open–source solver package designed to solve large–scale non–linear optimization problems. The results showed the potential for saving 47.12–103.83 MCM/year of water, increasing reservoir storage by up to 10.49%, and enhancing hydropower production by 6.10% to 13.79%.

Realizing the strengths of CP in handling complex constraints, flexibility, and combinatorial optimization, this study aims to apply a novel CP model and explore its capability for complicated multiple reservoir operation and their system constraints in the Chao Phraya River Basin (CPYRB) as shown in Fig. 1. CPYRB has transitioned from the naturally–uncontrolled basin to the highly–engineered system with multipurpose storage dams and extensive canal irrigation networks. Four interconnected storage dams; Bhumibol (BB), Sirikit (SK), Khwae Noi Bamrung Dan (KNB), and Pasak Jolasitr (PS) are jointly operated to satisfy the local and joint demands along the Chao Phraya River (CPYR) where the head flow is primarily fed by major tributaries including Ping, Wang, Yom, Nan and Pasak rivers. The controlled outflow from these dams takes approximately one day to reach local demand node. However, supplying water from dams to joint demand requires longer travel time of 2–10 days to reach the demand nodes. These four dams play a crucial role in regulating the reservoir outflow to jointly satisfy multiple water uses including water irrigation, industry, municipality, ecology, as well as hydropower generation in central Thailand. It is reported that more than 70% of the water allocated from these four dams is served for irrigation in the Greater Chao Phraya Irrigation Scheme (GCPYIS) occupying the irrigation service area of more than 10 million rai (16,000 km^2) (Kyaw et al. 2022; Sawangphol et al. 2024).

The Chao Phraya River Basin has several characteristics that make it challenging to apply conventional optimization methods at scale. These challenges include strong interconnections among four major reservoirs, diverse demand nodes, seasonal regulations governing allowable water deficits, tributary flow contributions, and flood–control restrictions that depend on anticipated inflows and changing

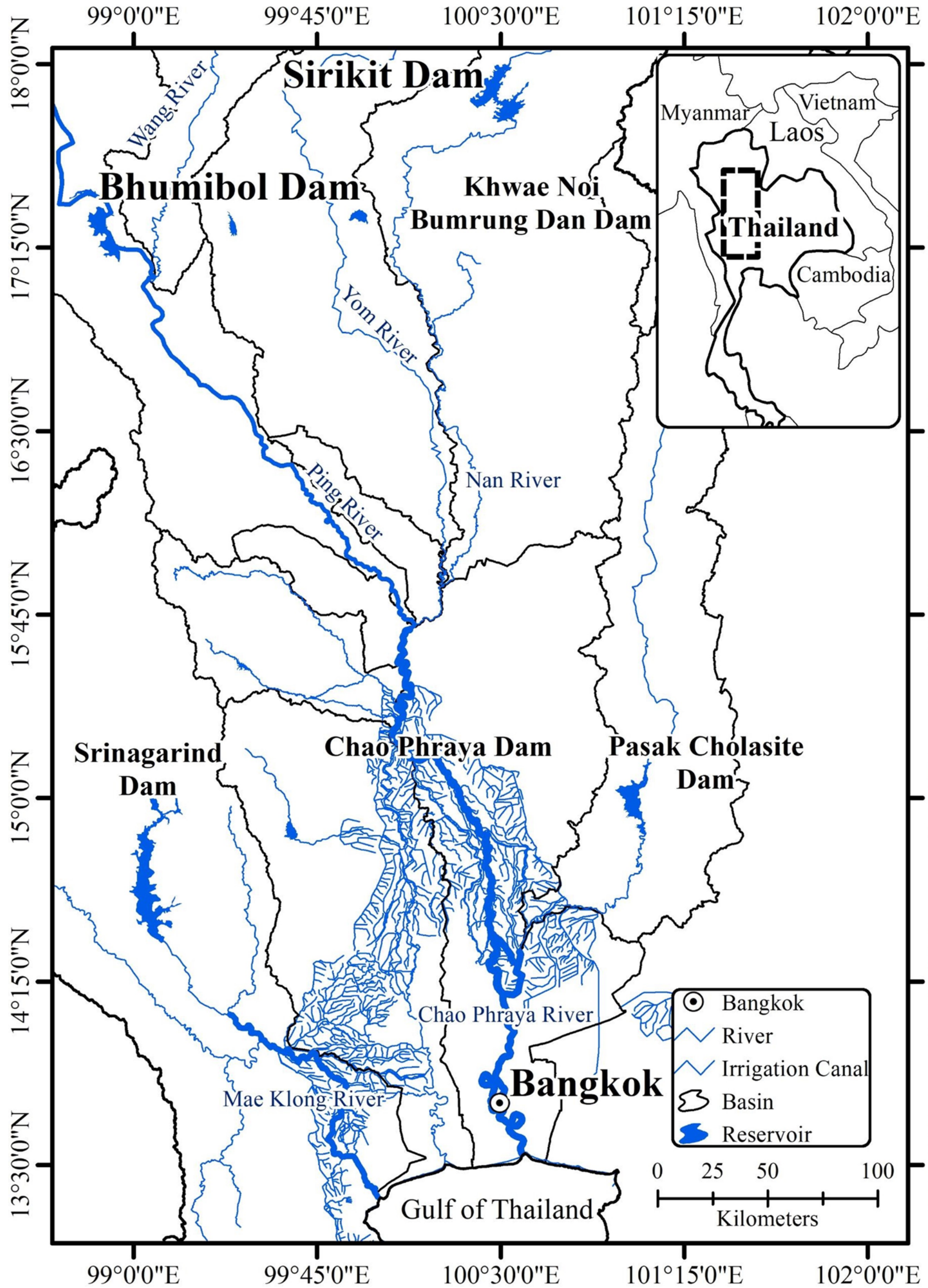

Fig. 1 The Chao Phraya River Basin in Central Thailand

storage levels. Additionally, significant travel time lags between reservoir releases and deliveries to irrigation and ecological nodes introduce complex temporal dependencies across multiple days. These factors create a high–dimensional, multi–objective, and highly constrained optimization problem. Other optimization approaches such as LP, NLP, DP, MHA, and fuzzy optimization have inherent limitations with respect to dimensionality, constraint management, or computational complexity. In contrast, CP is well–suited to this context, as it can encode numerous interrelated operational rules as explicit constraints. This allows CP to utilize constraint propagation to efficiently eliminate infeasible release patterns while exploring trade–offs among multiple objectives. For these reasons, CP was selected as the primary optimization framework for this study to formulate multi–reservoir operating policies in the CPYRB.

The varying water availability in major reservoirs exacerbated by regional climate variability, along with the uncontrolled expansion of seasonal cultivated area in GCPYIS and competing water demands from different sectors, has led to water scarcity especially during dry season (Nov.–Apr.) as evidenced in 2015, 2018, 2019, and 2020 (Kyaw et al. 2022). This water scarcity has caused a decline in crop yield, resulting in agricultural distress in the GCPYIS. Furthermore, the impact of seawater intrusion during drought periods when river water levels in the lower basin decrease, has amplified the severity of water scarcity. This has affected not only for agricultural sector but also the quality of drinking water supplied in the Bangkok Metropolitan Region. In addition, the frequent occurrence of tropical storms has increased risk of flooding in low–lying areas downstream of the Chao Phraya Diversion Dam particularly at the end of the year (Oct.–Nov.). Flooding significantly impacts local livelihoods and industrial estates in the central plains, thereby causing substantial economic losses at the national level particularly in the 2011 major flood. Furthermore, historical records from 2000 to 2024 indicate a frequent risk of the KNB and PS reservoirs reaching full capacity during the monsoon season, resulting in increased release volumes to deplete storage and ensure dam safety. These address a significant challenge of water resource management task, highlighting the necessity of effective and adaptive operational tools to improve complex multiple reservoir operation and create future water resilience in the CPYRB.

To moderate water scarcity in this basin, CP modelling using Python (GEKKO Optimization Suite) and IPOPT solver for multiple reservoir optimization in CPYRB were developed. The desired goal was to increase end–of–wet–season reservoir storage in Oct. to potentially supply irrigation water during dry planting season (Nov.–Apr.) in the GCPYIS. Developing a constraint programming model for a complex reservoir operation system in CPYRB using Python's GEKKO library with the IPOPT solver not only provides a user–friendly modeling environment but also guarantees effective and robust management of large–scale, nonlinear, and constrained optimization problems. GEKKO offers a python–based, object–oriented interface that enables mathematical formulations to be expressed concisely and readably. This supports rapid model development, simplifies debugging, and establishes a clear connection between reservoir optimization concepts and their computational execution. IPOPT employs an interior–point method using sparse linear algebra, which enhances its efficiency in addressing high–dimensional optimization challenges like multi–reservoir operation. This approach ensures convergence, even when the model incorporates nonlinear constraints such as travel time and release relationships. Since reservoir operation issues frequently involve nonlinear hydrological relationships and various operational constraints, IPOPT is well–equipped to handle these challenges. Furthermore, integrating GEKKO with Python allows for smooth data processing, visualization, and post–analysis, which is useful for scenario analysis and interpreting results. The effectiveness of CP in modelling and solving the complicated COPs for the multiple reservoir operation system in CPYRB was highlighted when the traveling time of released water from each reservoir to the water demand nodes was either included or excluded. This study contributes to the field of reservoir operation research by introducing a novel methodological approach that substitutes for traditional reservoir optimization techniques, particularly for large–scale, multi–objective, and multi–reservoir systems with complex constraints. Since the problem model is formulated separately from the solving algorithm, this leads to a reduction in development and computational time while achieving the model's multiple goals.

Methods

CP modelling for multiple reservoir optimization in CPYRB

Variable input and output terms and hypotheses identified for CP modelling

Two different types of CP models for multiple reservoir optimization in CPYRB were developed, including (1) CPM1: constraint programming model without incorporating travel time and (2) CPM2: constraint programming model incorporating travel time. CPM1 assumes that water released from upper reservoirs at time t can be supplied to fully meet the targeted water demand nodes at corresponding time t. In other words, it ignores the time delay for water to travel from the reservoirs to the demand points. This simplification reduces computational complexity but may miss short–term operational constraints caused by flow propagation. In contrast, CPM2 explicitly considers the travel time of reservoir water to reach the demand points, where time delays vary from 2 to 10 days. Consequently, the optimization process can ensure that reservoir water is released with proper timing to account for the hydraulic time delay before it reaches the different downstream demand nodes. By incorporating these temporal dynamics, CPM2 offers a more realistic portrayal of reservoir–river–demand node interactions, especially in situations where short–term release scheduling and joint coordination among operational offices for effective multiple reservoir operation are essential.

Variable inputs and outputs were identified for CP modelling as summarized in Table 1. The model inputs incorporate the reservoir water balance data, estimated water demand, relevant terms of hydropower generation system, and reservoir specifications of all reservoirs. While the model outputs are the optimal reservoir releases of all reservoirs obtained by the CP models. Optimization structures of the CPM1 and CPM2 models include objective functions, decision variables, and system constraints which were constructed using the same input dataset. However, the CPM2

Table 1 Definitions of variables and model types used in CP modeling

Variables	Definition	Unit
DELP	Local demand in the Lower Ping Water Distribution Zone (LPWDZ) includes both agricultural and non–agricultural water needs. Agricultural water is used in 4 operation and maintenance projects: Tor Thong Daeng, Wangbua, Wangyang, and Nongkhwan. Non–agricultural demand includes municipality, industry, and ecological water uses along the Lower Ping River	MCM
DELN	Local demand in the Lower Nan Water Distribution Zone (LPWDZ) includes both agricultural and non–agricultural water needs. Agricultural water is used in 5 operation and maintenance projects: Dongsetthee, Thabua, Plaichumpol, Naresuan and Yom–Nan. Non–agricultural demand includes municipality, industry, and ecological water uses along the Lower Nan River	MCM
DEKNB	Local demand includes both agricultural water in the Khwae Noi Bamrung Dan Operation and Maintenance Project and non–agricultural water needs	MCM
DEPS	Local demand includes both agricultural water in Pasak Jolasitr Operation and Maintenance Project and non–agricultural water needs	MCM
DECPY	Joint demand in the Chao Phraya Water Distribution Zone (CPYWDZ) includes both agricultural and non–agricultural water needs. Agricultural water is used in 26 operation and maintenance projects: Wat Sing, Bang Bal, Pollathep, Thabot, Samchuk, Donjedee, Phophraya, Borommathat, Chanasute, Yangmanee, Phak Hai, Maharaj, Manorom, Chong Kae, Khokkathiam, Roeng Rang, Southern Pasak, Nakhon Luang, Northern Rangsit, Southern Rangsit, Chaochet Bangyeehon, Phayabunlue, Prapimon, Pasicharoen, Klong Dan, and Praong Chao Chaiya Nuchit. Non–agricultural demand includes municipality and industry water uses along the Chao Phraya River	MCM
DEECON	Joint demand for ecological need along the Lower CPY River	MCM
D_t	Total water demand at time t	MCM
S^i_t and S^i_{t+1}	Reservoir water storage of reservoir i at time steps t and t + 1, respectively	MCM
I^i_t	Reservoir inflow of reservoir i at time step t	MCM
R^i_t	Optimal release of reservoir i at time step t achieved by two different types of CP model or model output	MCM
E^i_t	Evaporation losses of reservoir i at time step t	MCM
$Spill^i_t$	Spilled water from the reservoir i at time step t	MCM
R^i_{min} and R^i_{max}	Minimum and maximum releases to ensure the minimum environmental flow requirement and maximum safe channel capacity of reservoir i	MCM
S^i_{min} and S^i_{max}	Minimum and maximum storage capacity of reservoir i	MCM
SF^i_t	Potential side flow downstream of reservoir i	MCM
$SURC^i$	Water storage of reservoir i at the upper rule curve threshold	MCM
G^i_t	Energy production of reservoir i at time t	KWhr
Ht^i_t	Tail water head of reservoir i at time t	m msl
Hf^i_t	Reservoir water head of reservoir i at time t	m msl
e^i	Overall efficiency of hydropower plant of reservoir i	%
γ	Specific weight of water equal to 9.81 m/s^2	m/s^2
Δt	Working hour in a day of each hydropower plant	hr
CPM1	Constraint programming model without incorporating travel time	–
CPM2	Constraint programming model with incorporating travel time	–
DM	Demand model	–
$F_1(x)$	Objective function of the CPM1 model	–
$F_2(x)$	Objective function of the DM model	–
$F_3(x)$	Objective function of the CPM2 model	–
ED^i_t	Estimated total demands of reservoir i at time steps t for DM model	–
AWS_{DECPYt}	Expected available water storages in the reservoir system for joint demand node DECPY	–
$AWS_{DEECONt}$	Expected available water storages in the reservoir system for joint demand node DEECON	–

model considers predetermined travel time to optimize the dam releases, ensuring efficient and timely water delivery from dams to joint demand nodes.

The following hypotheses were adopted in this study to define COPs for the multiple reservoir operation within CPYRB:

(1) Local demands: DELP, DELN, DEKNB, and DEPS are individually supplied by BB, SK, KNB, and PS Dams, respectively.
(2) Joint demands: DECPY and DEECON are cooperatively supplied by BB, SK, KNB, and PS Dams.
(3) Total system demand (D) is the combination of local and joint demands.
(4) Water released from all dams should be equal to or greater than the targeted water demand in wet season when the water supply source in the reservoir is sufficient.
(5) Water released from all dams should be equal to or greater than 80% of the targeted demand in the dry season. This means 20% of the water deficit can be allowed during the dry season due to insufficient water supply in the reservoirs.
(6) In CPYRB, the dry season starts from Nov. to Apr. and the wet season runs from May. to Oct.
(7) 20% of potential side flow at W.4A and Y.17 runoff stations measuring the streamflow in the Wang and Yom Rivers are accounted, to help reduce the reservoir releases of BB and SK Dams, respectively (Charoenlerkthawin et al. 2021).
(8) According to the operational guidelines and current practices by EGAT, the minimum water releases of BB, SK, KNB, and PS Dams are specified according to the ecological need along the river downstream of each dam. While the maximum water releases of these dams are determined based on the safe channel capacity to avoid downstream flooding of each dam.
(9) Minimum water storage at the minimum pool levels of BB, SK, KNB, and PS Reservoirs are 3,800, 2,500, 36, and 3 MCM, respectively and maximum water storage at the maximum pool levels of BB, SK, KNB, and PS Reservoirs are 13,462, 9,510, 939, and 960 MCM, respectively.
(10) In this study, hydropower generation relies on the controlled releases of water from BB and SK reservoirs through their hydropower plants only.

Multiple reservoir optimization modelling

To formulate the COPs and develop CP models for complex multiple reservoir operation in CPYRB, the daily historical reservoir data of four major dams, namely, BB, SK, KNB, and PS, from 2000 to 2020, were collected and used as the inputs. The daily local and joint water demand data for the different water distribution zones, including agricultural and non–agricultural sectors, were accordingly estimated, namely, DELP, DELN, DEKNB, DEPS, DECPY, and DEECON. For the CPM2 model, the travel time of reservoir water released from dams to the CPY demand nodes was determined with 4, 6, 2 and 3 days for BB, SK, KNB, and PS Dams, respectively. In other words, the targeted joint demand at DECPY nodes is timely supplied when releasing water from dams prior to 4, 6, 2 and 3 days, respectively. In addition, the DEECON demand node is shared by four dams with travel time of 8, 10, 6 and 7 days for BB, SK, KNB, and PS Dams, respectively as graphically shown in Fig. 2.

The desired goal of multiple reservoir optimization developed by CP models is to increase water availability in the reservoir system particularly at BB and SK, two large storage dams at the end of the wet season (Oct.). Due to the uncontrolled increase in crop planting area expansion within CPYIS during the dry season (Nov.–Apr.), the additional water in reservoirs at the start of cultivation periods should be reserved to enhance water scarcity resilience. As downstream potential side flow from the river tributaries (Wang and Yom Rivers) is definitely high particularly during wet season (May.–Oct.), this leads to the ability to reduce reservoir releases from these two major dams due to substantial downstream side flow from river tributaries. Consequently, retaining savable water in reservoirs for subsequent use in the dry season can lead to an increased level of reservoir water storage before crop cultivation in the dry season starts. This study quantified the potential side flow at two key gauged stations, W.4A and Y.17 located downstream of BB and SK Dams, respectively, to reduce daily reservoir releases. Moreover, to prevent downstream flooding, system constraints indicating the operational practices of EGAT during critical floods, were included in the CP models.

In other words, the CP structures were fundamentally developed to bridge to physical hydrological processes by incorporating the reservoir water balance equation and downstream flow requirements to meet local and joint demands as fundamental constraints. The next–day water storage in the water balance equations is physically limited by the initial water storage plus the net inflows and net outflows across all reservoirs. In addition, the CP framework considers minimum and maximum downstream flow constraints, ensuring that the optimized release schedules from all reservoirs remain hydrologically feasible even under extreme climate variability, potential side flow, and varying reservoir storage levels.

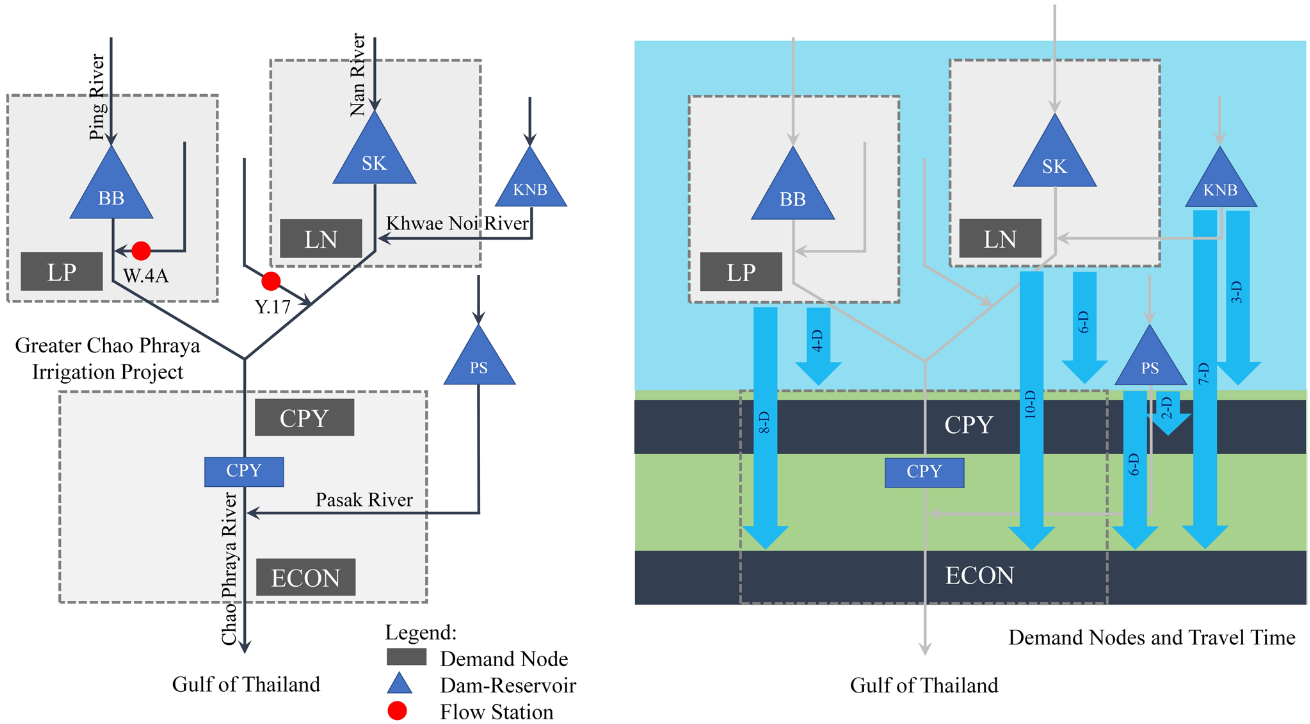

Fig. 2 A conceptual diagram showing dam–reservoir system, flow stations, demand nodes, and incorporated travel time of water for the CP–based multiple reservoir optimization in the CPYRB

CPM1: constraint programming model without incorporating travel time

CPM1 was designed when the targeted water demand input at time t was known and potentially supplied by the released water from all reservoirs at time t. To formulate the CPM1 model using GEKKO, a set of input and output variables (x_1, x_2, x_3, …, x_n) and their domains (D_1, D_2, D_3, …, D_n) were accordingly specified. Sets of system constraints (c_1, c_2, c_3, …, c_n) and objective functions ($f_1(x)$, $f_2(x)$, $f_2(x)$, …, $f_n(x)$) were subsequently defined for multi–objective optimization.

Objective function–CPM1

Objective function of the CPM1 model, $F_1(x)$ was specified by following equation;

$$F_1(x) = w_1 * minf_1(x) + w_2 * maxf_2(x) + w_3 * minf_3(x) + w_4 * maxf_4(x) \tag{1}$$

where weights assigned to each objective, w_1, w_2, w_3, w_4 lie between 0 and 1 and the summed weight is 1. In this study, the equally weighted objectives were determined for multi–objective optimization. $minf_1(x)$ is the minimization of water deficit, which is the sum of squared differences between CP releases of all reservoirs and targeted water demands over the entire operational time horizon as expressed in Equa. (2). The minimization of the absolute value of excessive releases during the refilled period over entire time steps, $minf_2(x)$, when the storage level exceeds the upper rule curve threshold and reservoir releases are substantially greater than the targeted water demand, is included in Equa. (3). In addition, maximization of next day storage at time t+1 of all reservoirs, $maxf_3(x)$, is also specified as given in Equa. (4). $minf_4(x)$ in Equa. (5) is the minimization of summed releases of all reservoirs over operational time steps.

$$\mathrm{minf_1}(x) = \sum_{t=1}^{T} (D_t^i - R_t^i)^2 \;; \forall i = 1, 2, \ldots, N, \& t = 1, 2, \ldots, T \tag{2}$$

$$\mathrm{minf_2}(x) = \sum_{t=1}^{N} \mathrm{abs}(S_t^i - \mathrm{SURC}^i) \,; \forall i = 1, 2, \ldots, N, \& t = 1, 2, \ldots, T \tag{3}$$

$$\mathrm{maxf_3}(x) = \max(S_{t+1}^i); \forall i = 1, 2, \ldots, N, \& t = 1, 2, \ldots, T \tag{4}$$

$$\mathrm{minf_4}(x) = \min\Big(\sum_{t=1}^{T} R_t^i\Big); \forall i = 1, 2, \ldots, N, \& t = 1, 2, \ldots, T \tag{5}$$

Decision variables–CPM1

Three decision variables for the CPM1 model needed to solve are; (1) daily water releases of all reservoirs at time t to satisfy targeted water demand at time t, (2) reservoir water storages of all reservoirs at time t+1, and (3) water allocation weights indicating the proportion of joint water demand proportionally supplied by each reservoir at time t.

CPM2: constraint programming model incorporating travel time

Supplying reservoir water to satisfy the targeted demand nodes temporally and spatially is influenced by the travel time taken from the dam to different demand nodes. Since the actual volume of water demand allocated by each reservoir at time step t is unknown due to the varying travel time of reservoir releases from dams to different demand nodes, consequently, modelling CPM2 model started with establishing the Demand Model (DM) to estimate the possible water demand for DECPY and DEECON nodes to be jointly supplied by all reservoirs at time t under the different travel time conditions of released water from dams. The CPM2 model, considering the corresponding travel times in the release constraints, was then integrated with DM to timely pre–release and sufficiently supply to meet the estimated water demand response.

Objective function–DM

The objective function of DM model, $F_2(x)$ aims to minimize the summed volumes of estimated total demands, ED_t^i including ED^i_{DECPYt} and $ED^i_{DEECONt}$ and local demand terms which will be timely allocated by reservoir i across all time steps as given in Equa. (6).

$$\mathrm{F2(x)} = \min(\sum_{t=1}^{T} \mathrm{ED}_t^i); \forall i = 1, 2, \ldots, N, \& t = 1, 2, \ldots, T \tag{6}$$

Decision variables–DM

The estimated joint demand weights for two joint demand nodes, DECPY and DEECON denoted as w^i_{DECPYt} and $w^i_{DEECONt}$ were defined as decision variables. The DM model uses these weights to consequently compute the estimated joint demand volumes, ED^i_{DECPYt} and $ED^i_{DEECONt}$ for reservoir i across all time steps. Furthermore, R^{BB}_{DELPt}, R^{SK}_{DELNt}, R^i_{DECPYt} and $R^i_{DEECONt}$ which are the reservoir releases to potentially supply for the estimated joint demand and local demand, were also defined as decision variables.

DM constraints

The DM constraints were identified in accordance with the expected available water storage constraints, AWS_{DECPYt} and $AWS_{DEECONt}$ in the reservoir system for joint demand nodes DECPY and DEECON, respectively as given in Equa. (7) and Equa. (8).

$$\mathrm{AWS_{DECPYt}} = \mathrm{AWS^{BB}_{DECPYt}} + \mathrm{AWS^{SK}_{DECPYt}} + \mathrm{AWS^{KNB}_{DECPYt}} + \mathrm{AWS^{PS}_{DECPYt}}; t = 1, 2, \ldots, T \tag{7}$$

$$\mathrm{AWS_{DEECONt}} = \mathrm{AWS^{BB}_{DEECONt}} + \mathrm{AWS^{SK}_{DEECONt}} + \mathrm{AWS^{KNB}_{DEECONt}} + \mathrm{AWS^{PS}_{DEECONt}}; t = 1, 2, \ldots, T \tag{8}$$

where AWS^i_{DECPY} and AWS^i_{DEECON} are the expected available water storages of reservoir i for joint demand nodes DECPY and DEECON, respectively when the reservoir release for each dam is proportionally allocated to meet the estimated joint demand volume, ED^i_{DECPYt} and $ED^i_{DEECONt}$ as well as its local demand and side flow constraints. These were constructed based on the reservoir water balance principle as expressed from the Equa. (9) to Equa. (20).

$$\mathrm{AWS^{BB}_{DECPYt}} = \mathrm{AWS^{BB}_{DECPYt-1}} + \{\mathrm{I^{BB}_t} - \mathrm{E^{BB}_t} - \mathrm{R^{BB}_{DELPt}} - \mathrm{ED^{BB}_{DECPYt+4}} + 0.2 * \mathrm{SF^{BB}_t}\}; for BB; t = 1, 2, \ldots, T \tag{9}$$

$$AWS^{SK}_{DECPYt} = AWS^{SK}_{DECPYt-1} + \{I^{SK}_t - E^{SK}_t - R^{SK}_{DELNt} - ED^{SK}_{DECPYt+6} + 0.2 * SF^{SK}_t\}; for SK; t = 1, 2, \ldots, T \tag{10}$$

$$AWS^{KNB}_{DECPYt} = AWS^{KNB}_{DECP-1} + \{I^{KNB}_t - E^{KNB}_t - R^{KNB}_{DEKNBt} - ED^{KNB}_{DECPYt+3}\}; for KNB; t = 1, 2, \ldots, T \tag{11}$$

$$AWS^{PS}_{DECPYt} = AWS^{PS}_{DECPYt-1} + \{I^{PS}_t - E^{PS}_t - R^{PS}_{DEPSt} - ED^{PS}_{DECPYt+2}\}; for PS \& t = 1, 2, \ldots, T \tag{12}$$

$$AWS^{BB}_{DEECONt} = AWS^{BB}_{DEECONt-1} + \{I^{BB}_t - E^{BB}_t - R^{BB}_{DELPt} - ED^{BB}_{DEECONt+8} + 0.2 * SF^{BB}_t\}; for BB; t = 1, 2, \ldots, T \tag{13}$$

$$AWS^{SK}_{DEECONt} = AWS^{SK}_{DEECONt-1} + \{I^{SK}_t - E^{SK}_{t-10} - R^{SK}_{DELNt} - ED^{SK}_{DEECONt+10} + 0.2 * SF^{SK}_t\}; for SK; t = 1, 2, \ldots, T \tag{14}$$

$$AWS^{KNB}_{DEECONt} = AWS^{KNB}_{DEECONt-1} + \{I^{KNB}_t - E^{KNB}_t - R^{KNB}_{DEKNBt} - ED^{KNB}_{t+7})\}; for KNB; t = 1, 2, \ldots, T \tag{15}$$

$$AWS^{PS}_{DEECONt} = AWS^{PS}_{DEECONt-1} + \{I^{PS}_t - E^{PS}_t - R^{PS}_{DEPSt} - ED^{PS}_{DEECONt+6})\}; for PS ; t = 1, 2, \ldots, T \tag{16}$$

$$R^{BB}_{DELPt} \geq DELP_t - 0.2 * SF^{BB}_t \ ; for\, BB \,\&\, t = 1, 2, \ldots, T \quad (17)$$

$$R^{SK}_{DELPt} \geq DELN_t - 0.2 * SF^{SK}_t \ ; for\, SK \,\&\, t = 1, 2, \ldots, T \quad (18)$$

$$R^i_{DECPYt} \geq w^i_{DECPYt} * ED^i_{DECPYt} \ ; \forall i = 1, 2, \ldots, N, \,\&\, t = 1, 2, \ldots, T \quad (19)$$

$$R^i_{DEECONt} \geq w^i_{DEECONt} * ED^i_{DEECONt} \ ; \forall i = 1, 2, \ldots, N, \,\&\, t = 1, 2, \ldots, T \quad (20)$$

where the estimated joint demand weights assigned by reservoir i at time step t is the ratio of expected available storage of reservoir i to expected available storage of all reservoirs at time step t as expressed in the Equa. (21) and Equa. (22). These estimated weights were then used in CPM2, a release model incorporating travel time.

$$w^i_{DECPYt} = \frac{AWS^i_{DECPYt}}{AWS_{DECPYt}} ; \forall i = 1, 2, \ldots, N, \,\&\, t = 1, 2, \ldots, T \quad (21)$$

$$w^i_{DEECONt} = \frac{AWS^i_{DEECONt}}{AWS_{DEECONt}} ; \forall i = 1, 2, \ldots, N, \,\&\, t = 1, 2, \ldots, T \quad (22)$$

Objective function–CPM2

Objective function of the CPM2 model, $F_3(x)$ in Equa. (23) is the minimization of the reservoir releases at time step t over operational time steps, which will be proportionally allocated by each reservoir under the different travel time conditions to meet both local and joint water demands.

$$F_3(x) = min\left(\sum_{t=1}^{T} R^i_t\right) ; \forall i = 1, 2, \ldots, N, \,\&\, t = 1, 2, \ldots, T \quad (23)$$

Decision variables–CPM2

Three decision variables for the CPM2 model are; (1) daily water demand volume proportionally shared by each reservoir at time t for the different demand nodes, and (2) water allocation weights of reservoir i (w^i_{DECPYt} and $w^i_{DEECONt}$) indicating the degree of joint water demand that should be proportionally supplied by each reservoir at time step t under the different travel time conditions.

System constraints–CPM1 & CPM2

The multiple reservoir operation system in CPYRB is primarily governed by the principle of mass balance. Consequently, the fundamental reservoir water balance constraint for all reservoirs was included in both CPM1 and CPM2 models as expressed in the Equa. (24);

$$S^i{}_{t+1} = S^i{}_t + I^i{}_t - R^i{}_t - E^i{}_t - Spill^i{}_t \ ; \forall i = 1, 2, \ldots, N, \&t = 1, 2, \ldots, T \quad (24)$$

The decision on reservoir releases in both CPM1 and CPM2 models are constrained by the minimum and maximum releases to ensure the minimum environmental flow requirement and maximum safe channel capacity of each dam as given in the Equa. (25). In addition, the available water storage after releasing water from each reservoir must lie between the minimum and maximum water storages, as expressed in Equa. (26).

$$R^i{}_{min} \leq R^i{}_t \leq R^i{}_max ; \forall i = 1, 2, \ldots, N, \&t = 1, 2, \ldots, T \quad (25)$$

$$S^i{}_{min} \leq S^i{}_t \leq S^i{}_{max} ; \forall i = 1, 2, \ldots, N, \&t = 1, 2, \ldots, T \quad (26)$$

To address flood control constraints specially at BB Dam during critical refilling periods, both the CPM1 and CPM2 models identified the system constraints using flood threshold levels established by EGAT for operational practice as detailed in the Equa. (27) to Equa. (30). In these constraints, reservoir releases were specified as a function of the predicted inflows (PI) at time step t which were developed using machine learning algorithms (Kraisangka et al. 2022).

$$R^{BB}_t \geq 0.3 * PI^{BB}_t | 12,157 \leq S^{BB}_{t-1} \leq 12,484; for BB \quad (27)$$

$$R^{BB}_t \geq 0.5 * PI^{BB}_t | 12,484 \leq S^{BB}_{t-1} \leq 12,810; for BB \quad (28)$$

$$R^{BB}_t \geq 0.7 * PI^{BB}_t | 12,810 \leq S^{BB}_{t-1} \leq 13,299; for BB \quad (29)$$

$$R^{BB}_t \geq PI^{BB}_t | 13,299 \leq S^{BB}_{t-1}; for BB \quad (30)$$

Since hydropower production is treated as a secondary objective in reservoir operation, maximization of energy is not defined and simulated energy results are not presented in this study. However, the hydropower production of BB and SK reservoirs is computed as the result of controlled releases discharging into the hydropower plants. Based on the analysis of hydropower production using historical energy records, the calibrated overall efficiencies of the hydropower plants were estimated, assuming 24 working hours in a day. Consequently, power constraints for both CPM1 and CPM2 models are given in the Equa. (31) and Equa. (32) where Q^i_t is the discharge rate of controlled release through hydropower plant measured in cubic meters per second.

$$G^i_t = e^i * \gamma * Q^i_t * H^i_t * \Delta t \ ; \forall i = 1, 2 \ (BB \,\&\, SK) \,\&\, t = 1, 2, \ldots, T \quad (31)$$

$$G^i_{min} \leq G^i_t \leq G^i_{max} ; \forall i = 1, 2 \ (BB \,\&\, SK) \,\&\, t = 1, 2, \ldots, T \quad (32)$$

The non–negative restriction on all variables of the problem was also defined in the constraint programming model as given in Equa. (33).

$$S^i_t, S^i_{t+1}, I^i_t, E^i_t, R^i_t, SF^i_t, G^i_t, Ht^i_t, \ Hf^i_t \geq 0 \quad (33)$$

Specific constraints–CPM1

For the specific constraints of CPM1 model, the travel time of reservoir releases to target demand nodes is not considered. Consequently, the release constraints from all dams highlighting the water scarcity resilience aspect are given in the Equa. (34) to Equa. (38) where the summed weights of all reservoirs at time step t are equal to 1.

$$R_t^{BB} \geq DELP_t + w_t^{BB}*DECPY_t + w_t^{BB}*DEECON_t - 0.2*SF_t^{BB};\ for\ BB \tag{34}$$

$$R_t^{SK} \geq DELN_t + w_t^{SK}*DECPY_t + w_t^{SK}*DEECON_t - 0.2*SF_t^{SK};\ for\ SK \tag{35}$$

$$R_t^{KNB} \geq DEKNB_t + w_t^{KNB}*DECPY_t + w_t^{KNB}*DEECON_t;\ for\ KNB \tag{36}$$

$$R_t^{PS} \geq DEPS_t + w_t^{PS}*DECPY_t + w_t^{PS}*DEECON_t;\ for\ PS \tag{37}$$

$$\sum_{i=1}^{N} w_t^i = w_t^{BB} + w_t^{SK} + w_t^{KNB} + w_t^{PS} = 1 \tag{38}$$

Specific constraints–CPM2

On the other hand, the travel time of reservoir releases to target demand nodes is considered in the specific constraints of CPM2 model for effective reservoir management. Consequently, the release constraints from all dams ensuring the ability to fully meet the targeted demand are represented in Equa. (39) to Equa. (44).

$$R_t^{BB} \geq DELP_t + w_{DECPYt}^{BB}*DECPY_{t+4} + w_{DEECONt}^{BB}*DEECON_{t+8} - 0.2*SF_t^{BB};\ for\ BB \tag{39}$$

$$R_t^{SK} \geq DELN_t + w_{DECPYt}^{SK}*DECPY_{t+6} + w_{DEECONt}^{SK}*DEECON_{t+10} - 0.2*SF_t^{SK};\ for\ SK \tag{40}$$

$$R_t^{KNB} \geq DEKNB_t + w_{DECPYt}^{KNB}*DECPY_{t+3} + w_{DEECONt}^{KNB}*DEECON_{t+7};\ for\ KNB \tag{41}$$

$$R_t^{PS} \geq DEPS_t + w_{DECPYt}^{PS}*DECPY_{t+2} + w_{DEECONt}^{PS}*DEECON_{t+6};\ for\ PS \tag{42}$$

$$\sum_{i=1}^{N} w_{DECPYt}^{i} = w_{DECPYt}^{BB} + w_{DECPYt}^{SK} + w_{DECPYt}^{KNB} + w_{DECPYt}^{PS} = 1; \forall i = 1, 2, \ldots, N at time t \tag{43}$$

$$\sum_{i=1}^{N} w_{DEECONt}^{i} = w_{DEECONt}^{BB} + w_{DEECONt}^{SK} + w_{DEECONt}^{KNB} + w_{DEECONt}^{PS} = 1; \forall i = 1, 2, \ldots, N at time t \tag{44}$$

The workflow diagram of the CPM1 and CPM2 optimization models for multiple reservoir operation in the CPYRB is presented in Fig. 3.

Evaluating the effectiveness of the CP model and water resilience in CPYRB

To evaluate the effectiveness of the CP models for reservoir optimization in CPYRB, the current multiple reservoir operation of BB and SK Dams from 2000 to 2021 were preliminarily analyzed. Since the KNB and PS Dams were started operating in 2009 and 2003 respectively, the

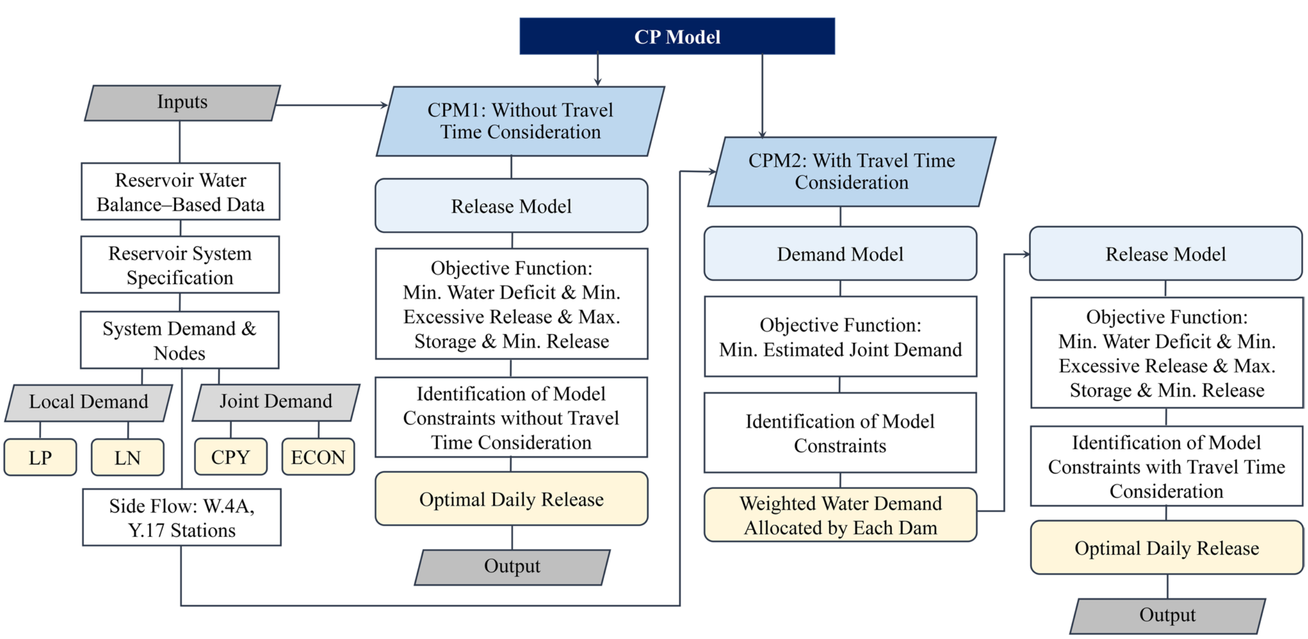

Fig. 3 Flowchart of the CP–based multiple reservoir optimization model framework in the CPYRB

reservoir optimizations were implemented from 2009 to 2021 for KNB Dam and from 2003 to 2021 for PS Dam. The analysis of daily and seasonal release ratios of four major dams obtained from the CPM1 model were conducted and compared with the current operation. In the final step, end–of–wet–season storages, annual reservoir releases, and increased water availability obtained from both the CPM1 and CPM2 models were investigated to evaluate water scarcity resilience potential and recommend release guideline trajectory for sustainable reservoir operation in CPYRB.

Result and discussion

Analysis of current multiple reservoir operation in CPYRB

To explore the current reservoir operation using rule curve as operational guideline in CPYRB, daily historical reservoir operation data from 1/1/2000 to 31/12/2021 were analyzed. The daily and seasonal release ratios from four main dams were investigated to determine short–term and long–term reservoir release schemes as shown in Table 2 and Fig. 4. It is found that the release ratios averaged from the daily long–term record were 0.36:0.45:0.06:0.13 for BB, SK, KNB, and PS, respectively indicating that 81% of water allocation was contributed by two large storage dams; BB and SK and the remaining 19% was contributed by KNB and PS. Within this, SK contributed a higher release portion compared to BB, PS, and KNB, respectively. In addition, the operational releases of all dams during critical wet year in 2011 and dry year in 2020, were also considerably investigated to exhibit the release schemes. In 2011, the release ratios for these four main dams were 0.32:0.40:0.12:0.16. This indicates that 28% of the total release was contributed from medium–sized reservoirs, KNB and PS which was substantially increased in comparison with the long–term operation. This operation was taken to protect against downstream flooding and avoid these two dams reaching full capacity for dam safety. Consequently, the major contribution from the large storage dams, BB and SK, decreased by 9% in the critical flood year of 2011. In 2020, the release ratios were adjusted to 0.31:0.55:0.10:0.04 for BB, SK, KNB, and PS, respectively indicating a 10% higher portion of released water from SK Dam compared to the long–term operation. It is also emphasized that two large storage dams, BB and SK still played an important role in supplying downstream water demand in critical dry years with an 86% contribution, which was higher than the long–term operation, while the remaining 14% was allocated from KNB and PS.

The analysis of seasonal release ratio among reservoirs illustrates that during the wet season, the average release ratios were 0.34:0.51:0.08:0.07, 0.32:0.42:0.08:0.18, and 0.34:0.42:0.06:0.18 in dry, normal, and wet years, respectively. Similarly, during the dry season, the average release ratios were 0.35:0.47:0.09:0.09, 0.40:0.47:0.05:0.08, and 0.46:0.47:0.03:0.04 in dry, normal, and wet years, respectively. Water released from the major storage dams, BB and SK, during dry season accounted for 82%, 87%, and 93% of the total releases from all dams in dry, normal, and wet years, respectively. However, their contribution shifted to 85%, 74%, and 76% during the wet season. It is noticeable that higher portion of water released from large reservoirs in dry season likely increased from dry to wet years due to the greater water availability potential in reservoirs. During the wet season of dry years, the portion of water released from BB and SK Dams was 3% higher than in the dry season of those same years. This increase was driven by the

Table 2 Operational release ratios obtained from the current reservoir operation and the CPM1 model

Release Ratio	Current Reservoir Operation				CPM1 Model without Travel Time Considerations			
	BB	SK	KNB	PS	BB	SK	KNB	PS
Daily Release Ratio								
LT[a/]	0.36	0.45	0.06	0.13	0.38	0.45	0.06	0.11
WY–2011	0.32	0.40	0.12	0.16	0.42	0.38	0.09	0.11
DY–2020	0.31	0.55	0.10	0.04	0.38	0.43	0.08	0.11
Seasonal Release Ratio								
WS[b/]								
• DY[c/]	0.34	0.51	0.08	0.07	0.39	0.49	0.05	0.07
• NY[c/]	0.32	0.42	0.08	0.18	0.32	0.46	0.06	0.16
• WY[c/]	0.34	0.42	0.06	0.18	0.32	0.53	0.03	0.12
DS[b/]								
• DY[c/]	0.35	0.47	0.09	0.09	0.41	0.41	0.12	0.06
• NY[c/]	0.40	0.47	0.05	0.08	0.43	0.42	0.07	0.08
• WY[c/]	0.46	0.47	0.03	0.04	0.49	0.42	0.03	0.06

Remark: [a/] LT represents a long–term operation/simulation starting from 1/1/2000 to 31/12/2021. [b/] WS is wet season (May.–Oct.) and DS is dry season (Nov. –Apr.). [c/] DY, NY, and WY are dry year, normal year, and wet year, respectively which are classified based on the established threshold of. reservoir inflow data of all dams specified by statistical analysis of historical records

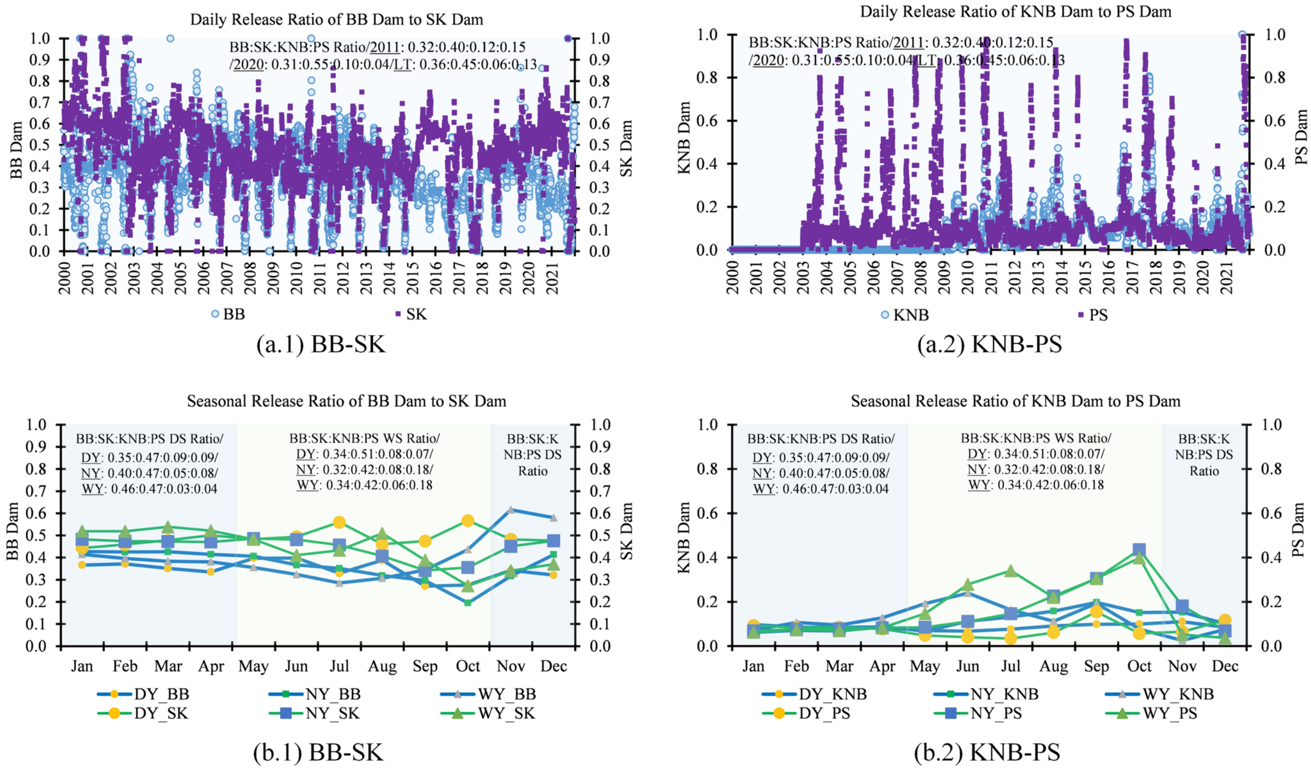

Fig. 4 Historical operational release ratios for BB–SK–KNB–SK Dams in the CPYRB, showing both daily and average monthly and seasonal data

large, uncontrollable cultivated area in the CPYIS combined with limited effective rainfall. Seasonal water releases from SK Dam were consistently higher than those from BB Dam across all water years, averaging 47% in the dry season and ranging between 42 to 51% in the wet season. This was primarily due to the larger reservoir inflow of SK, which varied from 3,818 to 11,227 MCM/yr from 2000 to 2020, even though the total reservoir capacity of SK Dam is about 41.56% smaller than BB Dam's. Conversely, the release contribution from BB Dam during the dry season increased, ranging from 35% in dry years to 46% in wet years. In contrast, this percentage contribution remained constant during the wet season, ranging from 32 to 34% across all water years.

Moreover, the percentages of release contribution from KNB and PS in the dry season were 18%, 13%, and 7% in dry, normal, and wet years, respectively, showing a decrease across the water year types. Conversely, for the wet season, the role of KNB and PS Dams increased, with their release portion shifting to 15%, 26%, and 24% in dry, normal, and wet years, respectively. Although the KNB and PS Dams have comparable storage capacities, PS significantly contributed the higher release during the wet season of the normal and wet years. However, the release portions of these two dams during the wet season of the dry years were relatively closer. Due to greater flash flood risk and high fluctuating inflows, PS Dam released more water than KNB Dam during the wet seasons of those water years to promptly empty the reservoir storage. However, the release portion remained constant over the dry season periods (Nov.–Apr.). The investigation reveals that the long–term average annual inflows for KNB and PS Dams were found to be 1,339 and 2,236 MCM/yr, respectively, which exceeded their reservoir capacity. These high volumes of reservoir inflow indicated a greater flood risk, especially during a critical wet year like 2011 for both KNB and PS Dams. Approximately 91.30% and 95.76% of the total inflow during critical wet years occurred in the wet season for KNB and PS Dams, respectively. Due to this greater flood risk, the analysis of reservoir release indicates that long–term annual releases for KNB and PS Dams were 1,305 and 2,030 MCM/yr which were very close to the annual inflows. In addition, the seasonal releases in wet season were still higher than in dry season particularly in normal and wet years to deplete the reservoir storages.

CP reservoir simulation results

CPM1: constraint programming model without incorporating travel time

Since travel time of water released from dams to targeted demand nodes is not considered for the release determination by the CPM1 model, the optimal sharing release ratios among dams at the same time steps can accordingly be generated. To compare with the current reservoir operation, the daily and seasonal release ratios are exhibited as shown in Table 2 and Fig. 5. For long–term operation, the CPM1 model recommended slightly increasing the release ratio of BB Dam and slightly decreasing the release ratio for the PS Dam. However, the release ratios for BB, SK, KNB, and PS Dams were 0.38:0.45:0.06:0.11, respectively which were very close to the current operation of 0.36:0.45:0.06:0.13. It is indicated from the CPM1 results that 83% of water allocation was contributed by two large storage dams, BB and SK, with the remaining 17% contributed by two medium storage dams, KNB and PS. While the majority of water allocation released from SK Dam remains similar to current operation, the CPM1 model indicates that the long–term operational role of BB was increased by + 2%, whereas water released from PS was decreased by –2%.

In critical flood and drought years, the CPM1 model demonstrated the different daily water release schemes by substantially increasing the contribution from BB Dam compared to the current operation. As a result, the release ratios for four main dams were altered to 0.42:0.38:0.09:0.11 in 2011 and 0.38:0.43:0.08:0.11 in 2020. It is revealed from the results of CPM1 that the major contribution for water allocation, particularly during the critical flood year in 2011, was from BB, which exceeded that of SK. This was due to the extremely peak annual inflow of BB, reaching 12,726 MCM/yr, which was + 13.36% higher than the reservoir inflow of SK in that year. Therefore, the CPM1 model presented more realistic daily release schemes for both BB and SK Dams, increasing the contribution of BB up to + 10% relative to the actual operation in 2011. To balance water availability and water storage levels in two large reservoirs, BB and SK during the critical drought year of 2020, the CPM1 model elevated the contribution of BB to release by + 7% due to higher initial water storage in prior year of 2019 while decreasing the contribution of SK by –13%, relative to the current operation. This led to a rational and realistic operation that achieved the long–term desired goal of CPM1 model in enhancing end–of–wet–season water storages in the reservoir system for irrigation purposes.

During both long–term and critical short–term operations, the CPM1 model consistently allocated 80% to 83% of water from BB and SK Dams, demonstrating its ability to manage water storage in large reservoirs. Conversely, current operation showed a wide fluctuation in release contribution from these dams which range from 75 to 86% depending on the varying water conditions. Consistent with the current operation during the wet season, the CPM1 model allocated a higher reservoir release for SK than BB, with the release ratios for BB, SK, KNB, and PS Dams of 0.39:0.49:0.05:0.07, 0.32:0.46:0.06:0.16, and

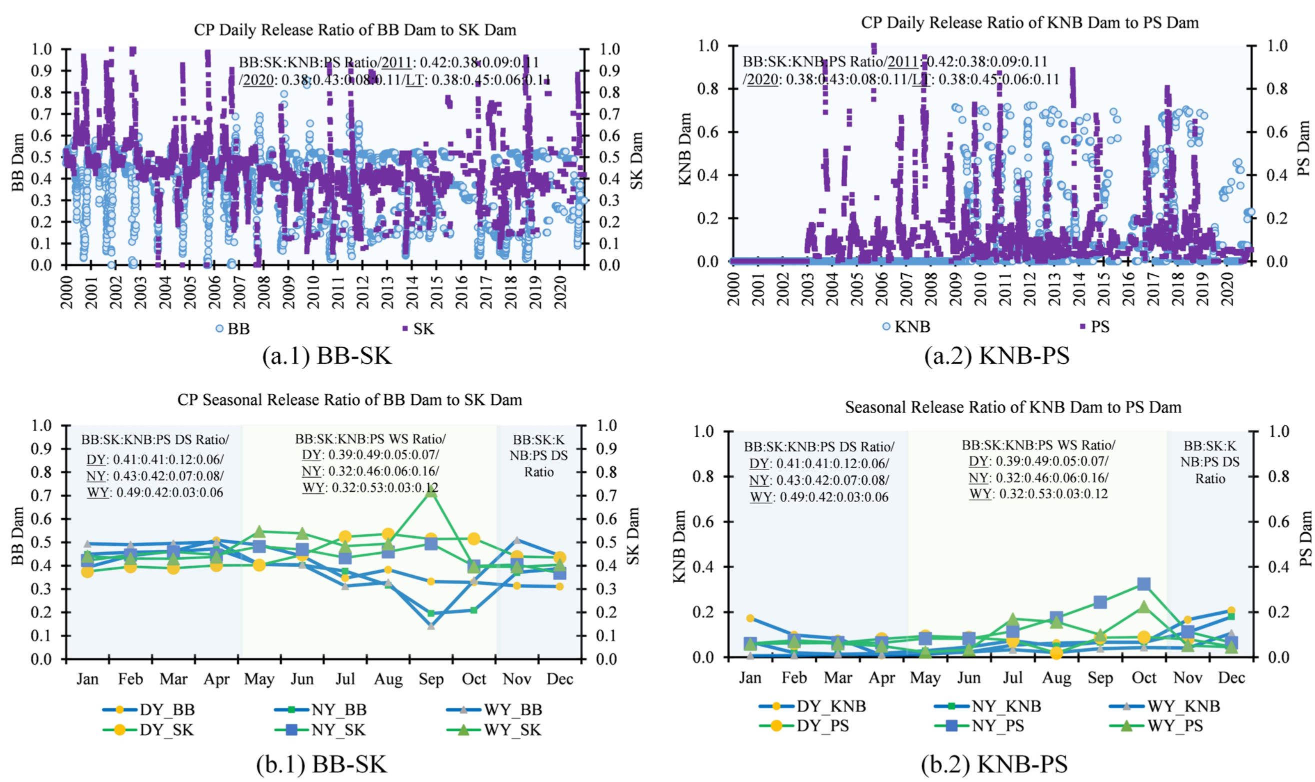

Fig. 5 Operational release ratios obtained from CPM1 model for BB–SK–KNB–SK dams in the CPYRB, showing both daily and average monthly and seasonal data

0.32:0.53:0.03:0.12 in dry, normal, and wet years, respectively. Importantly, during the dry season across water years, the proportion of water release supplied by BB Dam for the CPM1 model was substantially greater than or equal to that of SK Dam, with release ratios of 0.41:0.41:0.12:0.06, 0.43:0.42:0.07:0.08, and 0.49:0.42:0.03:0.06 in dry, normal, and wet years, respectively. This emphasizes that the contribution role of BB Dam in supplying water demands by the CPM1 was elevated during the wet season up to + 5% particularly in dry years in comparison to current operation. Moreover, the CPM1 model resulted in a substantial increase in reservoir release from BB Dam during the dry season across all water years, showing + 6% higher release in dry years, + 3% higher in normal years, and + 3% higher in wet years, compared to the current operation.

To emphasize the potential of increasing water availability in reservoirs at the beginning of dry season achieved by CPM1 model, the end–of–wet–season storages of all dams and annual releases were analyzed and compared with the current operation. The results of reservoir storage increase in both percentage and volume, are presented in Table 3. It is demonstrated that the CPM1 model could substantially increase water storage in BB and SK reservoirs by the end of wet season up to + 15.73% and + 16.36%, respectively in comparison with the current operation. In the other words, holding additional water of + 1,454 and + 1,258 MCM/yr in two large storage reservoirs before the dry season started by CPM1 model, could help moderate water scarcity over planting dry season. Conversely, the CPM1 model mostly resulted in a decrease in both average annual water storage and end − of − wet − season storage levels for KNB and PS reservoirs compared to current operation. Specifically, end − of − wet − season storage levels decreased by approximately − 12.20% and − 3.20%, respectively, resulting in volume reductions of − 89 and − 27 MCM/yr. This reduction was beneficial for flood control purposes, as the physical characteristics of these medium − sized dams limit their upper storage capacity to avoid flooding. In addition, due to higher annual releases in the reservoir system of + 123 MCM/yr during critical wet years, the CPM1 model could significantly lower the net storage levels at the end of wet season for all dams by –5.55%, –1.18% and –0.57% in 2002, 2006, and 2011, respectively. This resulted in a water storage reduction during critical wet years which varied from –141 to –1,245 MCM/yr compared to the observed water storages. Conversely, during critical dry years of 2014, 2015, 2019, and 2020, the long–term operation of the CPM1 model in the CPYRB led to an increase in net water storage for all dams at the end of wet season, ranging from + 25.36% to + 56.47%. Based on the long − term analysis, the average available water storage levels from 2000 to 2020 achieved by CPM1 model were kept up to 69.56%, 82.54%, 29.70%, and 53.45% of total storage capacity for BB, SK, KNB, and PS reservoirs, respectively. These values were mostly greater than those of the current operation for all dams except KNB, exhibiting a balancing management for both flood control and water scarcity in the region.

In terms of reservoir releases, the CPM1 model could provide similar annual release patterns for all reservoirs, showing small percentage discrepancies of average long − term annual releases of − 3.14%, − 2.92%, + 2.83%, and − 0.31% for BB, SK, KNB, and PS Dams, respectively. These figures are equivalent to release volume discrepancies of − 163, − 174, + 37, and − 6 MCM/yr for BB, SK, KNB, and PS Dams, respectively. In addition, the average annual release volumes of all reservoirs for both current operation and CPM1 model varied substantially across water years, indicating small volumes in dry years and larger volumes in wet years. It is investigated that the average long − term and accumulated annual releases for KNB, as simulated by the CPM1 model, were slightly greater than the current operational releases, while the annual releases for PS were slightly less. This difference is beneficial for flood control operation at medium − size reservoirs, as the available water storages for KNB and PS were properly maintained at 67.94% and 85.31% of their storage capacities, respectively, at the end of the wet season. This reduced flood risks while reserving water for the subsequent planting dry season. Moreover, it is revealed that the daily release schemes among reservoirs in the system were significantly altered driven by the multiple goals of CPM1 model, system constraints, water demand conditions and specific model settings within the CPYRB. This resulted in changes and fluctuations in long − term annual releases among reservoirs in comparison to the current operation, considerably varying from − 37.67% to + 38.47% for BB, − 71.68% to + 33.04% for SK, − 54.60% to + 46.79% for KNB, and − 33.23% to + 18.71% for PS. Consequently, these fluctuations led to substantial changes in end − of − wet − season storages in all reservoirs. However, average long–term annual releases for CPM1 were not significantly different from the current operation. This guarantees that employing the CPM1 model for reservoir optimization in CPYRB could help ensure increased water storage levels, indicating its capability to manage water scarcity as water demand rises. Furthermore, these daily release schemes of all reservoirs achieved by the CPM1 model can be used to establish weekly, monthly, and seasonal release trajectory guidelines and annual water allocation plans to support the planning task of the reservoir system.

Remark: Operational periods for KNB, and PS Dams have started since 2009 and 2003, respectively.

Table 3 CP simulated results for multiple reservoir optimization in CPYRB

Year	Water Year	Avg. End–of–Wet–Season Storage (MCM)								Annual Release (MCM)							
		Observed Storage				CP Storage				Observed Release				CP Release			
		BB	SK	KNB	PS	BB	SK	KNB	PS	BB	SK	KNB	PS	BB	SK	KNB	PS
CPM1 Model without Travel Time Consideration																	
2000	NY	11,083	9,389	–	–	10,517	9,510	–	–	3,413	5,851	–	–	4,160	5,642	–	–
2001	NY	11,377	9,361	–	–	9,897	9,510	–	–	4,006	7,300	–	–	4,772	7,434	–	–
2002	WY	13,300	9,121	–	–	11,666	9,510	–	–	5,860	6,447	–	–	5,179	6,690	–	–
2003	NY	9,701	8,321	–	817	10,316	8,449	–	543	7,878	6,791	–	1,712	6,385	6,487	–	2,074
2004	NY	8,384	9,335	–	820	9,189	9,510	–	620	4,742	6,248	–	1,784	4,998	5,712	–	1,801
2005	NY	10,065	8,609	–	853	9,949	9,510	–	597	4,339	6,568	–	720	4,806	6,322	–	685
2006	WY	13,291	9,458	–	916	13,063	9,510	–	813	6,378	6,325	–	3,087	5,684	7,078	–	2,897
2007	NY	11,415	7,446	–	980	12,858	8,484	–	712	7,877	6,737	–	2,462	6,326	5,730	–	2,471
2008	NY	9,085	8,301	–	953	12,528	9,510	–	849	6,791	6,253	–	2,727	5,651	6,460	–	2,615
2009	NY	9,347	6,023	558	946	13,462	9,451	417	960	6,892	6,716	921	2,144	5,006	3,912	1,731	1,933
2010	NY	8,494	7,784	780	976	13,080	9,509	724	960	5,140	3,932	1,196	3,261	4,941	5,872	1,341	3,278
2011	WY	13,394	9,495	942	1,021	13,462	9,510	780	959	7,589	9,396	2,900	4,469	12,334	11,028	2,986	4,667
2012	NY	8,675	6,587	732	778	10,477	6,742	113	775	9,185	8,153	1,211	1,146	7,819	8,224	1,103	1,150
2013	NY	7,061	5,932	895	963	9,090	6,899	939	960	4,303	4,285	1,533	2,110	3,877	3,700	1,110	1,902
2014	DY	6,025	5,841	784	817	8,583	7,918	768	960	3,939	4,300	924	1,151	3,662	3,390	767	1,158
2015	DY	4,984	4,906	413	640	6,830	7,704	365	927	2,680	4,712	792	846	3,443	3,767	857	635
2016	NY	6,805	7,657	946	985	8,211	9,510	939	960	1,451	3,103	967	2,096	1,830	3,895	1,147	2,419
2017	NY	10,564	8,389	975	958	11,804	9,510	939	960	2,726	4,716	2,663	3,706	2,604	5,309	3,171	3,605
2018	NY	9,706	8,348	740	741	11,655	9,510	656	960	6,193	7,448	1,163	2,297	5,417	7,218	978	2,192
2019	DY	5,934	5,294	496	351	9,395	8,552	507	440	5,628	6,169	756	547	4,194	4,419	489	673
2020	DY	5,464	5,819	463	709	8,659	9,508	514	782	2,158	3,811	641	277	2,657	3,315	429	274
Avg		**9,246**	**7,686**	**727**	**846**	**10,700**	**8,944**	**638**	**819**	**5,198**	**5,965**	**1,306**	**2,030**	**5,035**	**5,791**	**1,343**	**2,024**
Volume Increased (MCM)						**+1,454**	**+1,258**	**–89**	**–27**					**–163**	**–174**	**+37**	**–6**
Percent Increase (%)						**+15.73**	**+16.36**	**–12.20**	**–3.20**					**–3.14**	**–2.92**	**+2.83**	**–0.31**
CPM2 Model with Travel Time Consideration																	
2000	NY	11,083	9,389	–	–	10,230	9,000	–	–	3,413	5,851	–	–	4,484	5,973	–	–
2001	NY	11,377	9,361	–	–	9,046	8,898	–	–	4,006	7,300	–	–	5,322	7,511	–	–
2002	WY	13,300	9,121	–	–	10,362	8,978	–	–	5,860	6,447	–	–	5,699	6,474	–	–
2003	NY	9,701	8,321	–	817	8,288	8,663	–	950	7,878	6,791	–	1,712	6,880	5,843	–	1,608
2004	NY	8,384	9,335	–	820	7,673	8,935	–	927	4,742	6,248	–	1,784	4,467	6,572	–	1,763
2005	NY	10,065	8,609	–	853	8,952	8,987	–	953	4,339	6,568	–	720	4,446	6,209	–	864
2006	WY	13,291	9,458	–	916	12,296	8,995	–	960	6,378	6,325	–	3,087	5,399	7,052	–	3,060
2007	NY	11,415	7,446	–	980	11,877	8,911	–	960	7,877	6,737	–	2,462	6,631	4,732	–	2,316
2008	NY	9,085	8,301	–	953	11,126	8,933	–	960	6,791	6,253	–	2,727	5,813	7,399	–	2,852
2009	NY	9,347	6,023	558	946	11,872	7,994	939	960	6,892	6,716	921	2,144	5,569	5,016	524	2,015
2010	NY	8,494	7,784	780	976	11,130	8,915	939	960	5,140	3,932	1,196	3,261	5,524	5,087	1,340	3,278
2011	WY	13,394	9,495	942	1,021	12,214	8,917	939	959	7,589	9,396	2,900	4,469	11,497	11,172	3,070	4,607

Table 3 (continued)

Year	Water Year	Avg. End–of–Wet–Season Storage (MCM)								Annual Release (MCM)							
		Observed Storage				CP Storage				Observed Release				CP Release			
		BB	SK	KNB	PS	BB	SK	KNB	PS	BB	SK	KNB	PS	BB	SK	KNB	PS
2012	NY	8,675	6,587	732	778	8,063	7,738	939	941	9,185	8,153	1,211	1,146	8,563	6,402	1,065	1,019
2013	NY	7,061	5,932	895	963	7,329	7,901	939	960	4,303	4,285	1,533	2,110	3,533	3,824	1,429	2,118
2014	DY	6,025	5,841	784	817	7,022	8,586	939	960	3,939	4,300	924	1,151	3,255	3,595	1,033	1,133
2015	DY	4,984	4,906	413	640	5,510	7,981	875	959	2,680	4,712	792	846	3,187	4,157	553	631
2016	NY	6,805	7,657	946	985	6,875	8,992	939	960	1,451	3,103	967	2,096	2,015	4,847	1,352	2,387
2017	NY	10,564	8,389	975	958	9,813	8,995	939	960	2,726	4,716	2,663	3,706	3,544	5,423	2,650	3,660
2018	NY	9,706	8,348	740	741	9,557	8,745	939	960	6,193	7,448	1,163	2,297	5,304	7,257	1,030	2,139
2019	DY	5,934	5,294	496	351	7,251	8,092	934	722	5,628	6,169	756	547	4,109	4,050	535	421
2020	DY	5,464	5,819	463	709	6,740	8,467	939	960	2,158	3,811	641	277	2,413	3,975	577	430
Avg		**9,246**	**7,686**	**727**	**846**	**9,201**	**8,649**	**933**	**943**	**5,198**	**5,965**	**1,306**	**2,030**	**5,126**	**5,837**	**1,263**	**2,017**
Volume Increased (MCM)						**−44**	**+962**	**+206**	**+97**					**−72**	**−128**	**−42**	**−13**
Percent Increase (%)						**−0.48**	**+12.52**	**+28.39**	**+11.48**					**−1.38**	**−2.15**	**−3.25**	**−0.66**

CPM2: constraint programming model incorporating travel time

The end–of–wet–season storages of all dams and annual releases accomplished by the CPM2 model were analyzed. Compared to the current operation as shown in Fig. 6, the CPM2 model resulted in increased water storage levels in SK, KNB, and PS reservoirs at the end of wet season up to + 12.52%, + 28.39% and + 11.48%, respectively. However, storage in BB reservoir slightly decreased by − 0.48%. In terms of storage volumes, these figures showed discrepancies of − 44, + 962, + 206, and + 97 MCM/yr for BB, SK, KNB and PS Dams, respectively. In other words, the increased volume of total water storage achieved by the CPM2 model was approximately + 1,265 MCM/yr enhancing drought risk mitigation especially during critical dry years of 2014, 2015, 2019, and 2020 when reservoir storages in all dams were substantially increased. Compared with the CPM1 model, the end–of–wet–season storage patterns by CPM2 model from 2000 to 2020 for the BB and SK Dams were likely similar, but their patterns were apparently different for the KNB and PS Dams. It is revealed that CPM2 provided lower end–of–wet–season storage levels of − 16.26% and − 3.41% at BB and SK Dams, respectively while providing higher end–of–wet–season storage levels of + 31.62% and + 3.15% at KNB and PS Dams compared to CPM1 model. However, the CPM2 model resulted in a considerable decrease in end–of–wet–season storage levels in the reservoir system with discrepancy of –1,375 MCM/yr compared to CPM1 model to help moderate flooding. In addition, during the critical wet years of 2002, 2006, and 2011, the CPM2 model substantially lowered the end–of–wet–season storage levels in the four dams by − 13.74%, − 5.98%, and − 7.34%, respectively, in comparison to the current operation. Compared to the CPM1 model, the CPM2 model provided larger reservoir vacancy to handle flooding in critical wet years. In contrast, during critical dry years of 2014, 2015, 2019, and 2020, the long–term operation of the CPM2 model led to an increased volume in net water storage across all dams at the end of wet season, ranging from + 30.00% to + 40.78% compared to the current operation. This was slightly lower than those obtained from CPM1 model. However, it enhanced the ability to efficiently supply irrigation water from dams throughout the cultivation periods during dry years. This was due to increased water availability in reservoirs at the beginning of the dry season, especially during critical dry years. This operation reflects effective management to cope with flooding, as the CPM2 properly maintained reservoir storage space corresponding to high varying inflows. Moreover, based on the long − term analysis to recognize and exhibit reservoir depletion as a means to moderate flooding, the average available water storage levels from 2000 to 2020

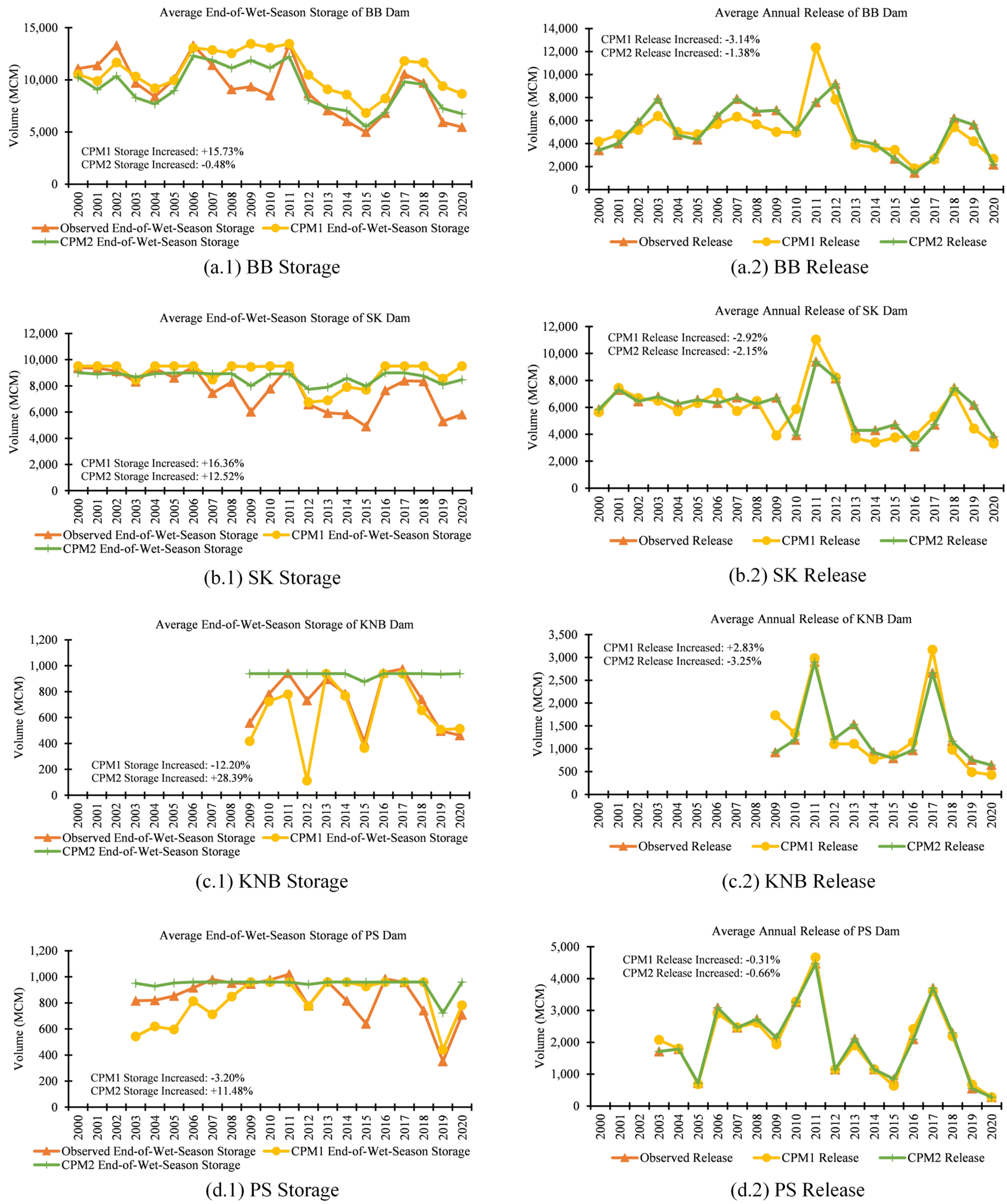

Fig. 6 Comparison of end–of–wet–season storages and annual reservoir releases of BB–SK–KNB–SK dams obtained from CP models and observed data

of CPM2 model were kept up to 57.78%, 79.55%, 85.25%, and 78.40% of total storage capacity for BB, SK, KNB, and PS reservoirs, respectively. These storage levels generally lie below the average value of designed Upper Rule Curve (URC) of each dam, thus demonstrating a balancing management strategy for both flood control and water scarcity.

In terms of long–term annual releases, the CPM2 model more closely replicated the current operation patterns than the CPM1 model across all dams. The small percentage differences of their average values compared to the current operation were –1.38%, –2.15%, –3.25%, and –0.66% for BB, SK, KNB, and PS, respectively. It is also exhibited that the annual release patterns done from CPM2 model were really close to CPM1 model with the discrepancy of + 1.78%, + 0.79, –6.33%, and –0.35% BB, SK, KNB, and PS, respectively. In other words, the CPM2 recommended supplying higher annual release volumes for BB and SK Dams but slightly lower volumes for KNB and PS Dams. Similar to current operation and the CPM1 model, the average annual release volumes of all reservoirs for CPM2 model varied substantially across water years, indicating smaller volumes in dry years and larger volumes in wet years. Compared to the current operation, the total release volumes in all reservoirs obtained from CPM2 model were –15.50%, –2.73%, and + 8.79%, during dry, normal, and wet years respectively. In comparison, the total release volumes in all reservoirs as the results of CPM1 model were –15.24%, –3.32%, and + 9.18% during dry, normal, and wet years, respectively. The decreases in annual releases from these two models particularly during critical dry years reasonably led to a substantial increase in water storage at the end of wet season. Conversely, the significant increases in annual release during wet years relatively resulted in the considerable decreases in reservoir water storages. Furthermore, these operations by the CP models were in accordance with the fluctuation of total reservoir inflows in the reservoir system, which varied from smaller values in dry years to greater values in wet years.

Similar to the results of the CPM1 model, it is found that the daily release schemes among reservoirs in the system were significantly adjusted in response to the multiple goals of the CPM2 model, system constraints, water demand conditions, and specific model settings within the CPYRB. This led to substantial changes and high fluctuations in long − term annual releases among reservoirs, with a wide range from − 36.97% to + 33.99% for BB, − 52.32% to + 35.98% for SK, − 75.76% to + 28.48% for KNB, and − 34.07% to + 35.58% for PS, respectively, compared to the current operation. However, the average value of long − term annual releases obtained by the CPM2 model showed only a small discrepancy in comparison with the current operation. This operation recommended by the CPM2 model consequently resulted in substantial changes in end–of–wet–season storages in the reservoir system, thereby ensuring higher water storage levels to mitigate water scarcity during the planting season.

The explicit integration of travel time significantly changes the optimization process compared to CPM1. In CPM1, it is assumed that releases from each reservoir at time step t are instantly available to meet local and joint demands at the same time step. This simplification enables the model to respond directly to current demand and side–flow conditions, often prioritizing maximizing end–of–wet–season storage while satisfying aggregate demand in each period. However, in CPM2, water released from the BB, SK, KNB, and PS reservoirs contributes to meeting joint demand only after a delay of 2 to 10 days. This is reflected in the adjusted demand terms in the Demand Model and the release constraints. Consequently, CPM2 must pre–release water several days in advance to ensure that the required volumes reach the DECPY and DEECON nodes in alignment with demand schedules. This anticipatory approach links current release decisions to future storage and demand conditions. It results in smoother and earlier release patterns, especially during the transition between wet and dry seasons, but limits the ability to maximize terminal storage to the same degree as CPM1. Therefore, the resulting release sequences demonstrate a careful trade–off between maintaining end–of–wet–season storage and ensuring timely, consistent water deliveries to downstream irrigation and ecological demand nodes.

Evaluation of water resilience in CPYRB

Water resilience for reservoir operation refers to the ability of the reservoir systems to recover from water stress challenges and adjust their systems to handle future water scarcity and flood risks. This ensures reliability of water supply source in reservoirs and provides effective flood control measures under varying climate conditions and rising water demand (Wang and Blackmore 2009). In this study, a comparison of the CPM1 and CPM2 simulated operational results highlighting importance of water scarcity resilience in the CPYRB, was conducted. It is demonstrated that both models potentially secured resilience by increasing water availability in reservoirs prior to the start of cultivation periods in dry season (Nov.) with 2,712 and 1,265 MCM/yr, respectively as shown in Fig. 7. Compared to the water demand in dry season (Nov.–Apr.) from 2009 to 2020 when four main dams were fully operated, the reservoir operation system exhibited effective recovery from water scarcity particularly in critical dry years (2015 and 2018–2020) due to increased water availability in reservoirs to supplement the existing supply. This indicates that reservoir operation

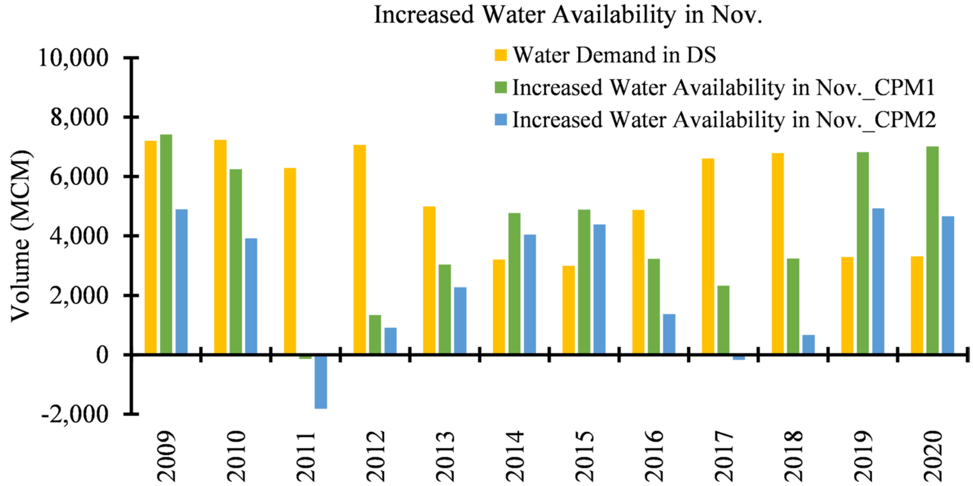

Fig. 7 Comparison of dry season water demand with increased water availability accomplished by CP models at the start of the dry season (Nov.)

system could be restored to the normal state after encountering water scarcity by reason of uncontrolled expansion of rising cultivated area size during the dry season.

Because of the different manners of optimization structures, time–dependent side flow conditions, and travel time factors considered, the CPM1 and CPM2 models generated different daily release schemes for long–term operation covering extreme weather events in the basin. However, the end–of–wet–season storages for BB and SK Dams especially in dry and normal years were significantly increased by both CPM1 and CPM2 models which were beneficial for mitigating water scarcity in subsequent planting seasons. Furthermore, these developed models could properly maintain available water storage levels over a year in an acceptable range of flood control risks for all dams particularly in critical wet years in 2002, 2006, and 2011. Consequently, this operation, in particular the CPM1 model, helps moderate the flood risks of sudden full reservoir filling, especially at KNB and PS Dams, during the monsoon season. However, reservoir storage levels in all dams were substantially increased by the end of wet season to supply water throughout the dry season. This reflected the enhanced flood resilience and improved reservoir operation performances for water scarcity in CPYRB when the CPM1 and CPM2 models were deployed. By incorporating travel times between releases from different dams and the various demand nodes, CPM2 offered more realistic and effective operations to timely and spatially distribute water in the irrigation farm area than CPM1. This ensured that water was supplied at various water distribution zones at the right time of use while satisfying system–wide objectives and time–dependent constraints. Since CPM1 model neglected the travel time in modelling process and generated similar patterns of end–of–wet–season storages for all dams compared to the observed operation, the lumped reservoir water allocated from all dams at the same time steps might possibly result in untimely irrigation within the GCPYIS. This possibly impacted the field level irrigation efficiency leading to water stress and reduced crop yield production of specific crops.

The differing behaviors of CPM1 and CPM2 illustrate a significant trade–off between maximizing storage and ensuring operational practicality. CPM1, which overlooks travel time, manages to retain more water in the major storage reservoirs by the end of the wet season, representing the maximum potential for system–wide resilience against water scarcity based on storage levels. However, this approach has the drawback of ignoring the time lag between water releases and actual downstream demand, which can lead to delayed water deliveries and misalignment between reservoir releases and crop water needs in irrigation areas. On the other hand, CPM2 forgoes some of the potential storage capacity in the BB and SK reservoirs to better accommodate travel–time–dependent demand satisfaction. This strategy also allows the maintenance of larger storage vacancies in KNB and PS for flood risk mitigation. As a result, the release patterns from CPM2 align more closely with operational practices, thereby addressing the timing of irrigation deliveries and the need to preserve flood–control capacity in flood–prone downstream areas. In summary, CPM1 and CPM2 represent alternative operational strategies that exist on a continuum, balancing the goal of maximizing water storage at the end of the wet season with the need for a realistic and implementable operating policy.

Comparative analysis of CP models with other optimization approaches

To investigate the competency of CP models for large–scale multiple reservoir operation in CPYRB, a comparative analysis was accordingly conducted. This analysis compared the simulated annual releases achieved by the CPM1 and CPM2 models for BB and SK Dams with those of other optimization techniques previously studied in CPYRB, using the same datasets and similar system constraints. Three main

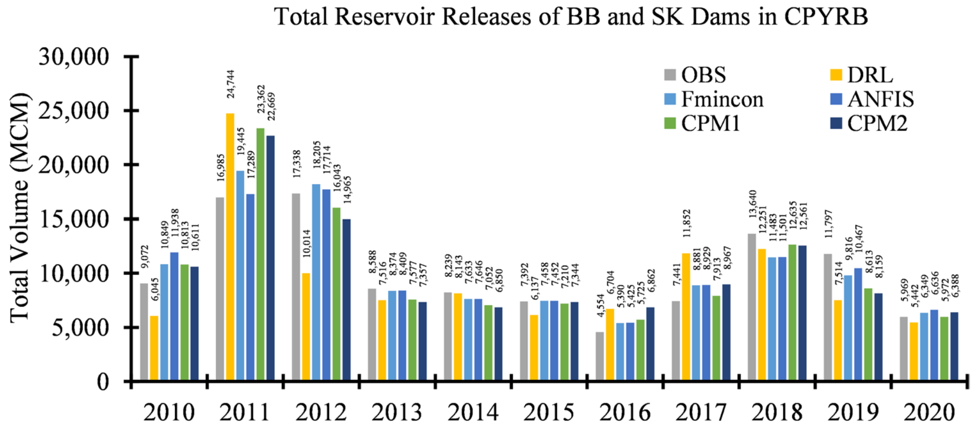

Fig. 8 Comparison of total reservoir releases for BB and SK Dams from the DRL–Fmincon–ANFIS–CP models

Table 4 Statistical correlation of total reservoir releases for BB and SK Dams compared to CP models and other optimization techniques

	OBS	DRL	Fmincon	ANFIS	CPM1	CPM2
OBS	1					
DRL	0.6744	1				
Fmincon	0.9481	0.7525	1			
ANFIS	0.9497	0.6690	0.9890	1		
CPM1	0.8924	0.8684	0.9611	0.9258	1	
CPM2	0.8541	0.8975	0.9394	0.8972	0.9945	1

techniques were selected including Deep Reinforcement Learning (DRL) (Phankamolsil et al. 2025), non–linear optimization programming (Kyaw et al. 2022), and Adaptive Neuro Fuzzy Inference System (ANFIS) (Kyaw et al. 2024) applied for reservoir optimization in CPYRB. The multi–agent–based DRL model was constructed using deep deterministic policy gradient algorithm, to provide comprehensive and flexible plans for reservoir operation planning in the CPYRB aiming to mitigate flood and drought risks. The non–linear optimization technique using Fmincon function was adopted for BB and SK reservoir operation system to address water scarcity in the basin. In addition, the ANFIS–based reservoir operation model for BB and SK Dams was also developed to aid the reservoir operation system in water scarcity and flood moderation. The comparison of observed (OBS) and simulated annual reservoir releases for BB and SK Dams using DRL, Fmincon, ANFIS, and CP models, is presented in Fig. 8.

It is revealed that the CPM1 and CPM2 models generated the similar long–term annual release patterns of the two main storage dams with other optimization techniques. The statistical correlation of total annual releases between CPM1 and CPM2 models was very close to each other, with a correlation coefficient of 0.9945, although the release ratios for BB and SK Dams achieved by the CPM1 and CPM2 models were substantially different. The CPM1 model generally exhibited a closer correlation with current operation and other optimization techniques than the CPM2 model. These correlation coefficients were 0.8924, 0.8684, 0.9611, and 0.9258 for observed releases, DRL, Fmincon, and ANFIS, respectively. For the CPM2 model, most of these correlation coefficients were slightly lower specifically 0.8541, 0.8975, 0.9394, and 0.8972 for observed releases, DRL, Fmincon, and ANFIS, respectively as presented in Table 4. However, these two types of CPM models showed the strongest correlation with non–linear optimization programming using fmincon function. Compared to the current operation, the percentage differences in average total releases performed by the different optimization models were –4.19% (DRL), +2.58% (Fmincon), +2.15% (ANFIS), +1.71% (CPM1), and +1.55% (CPM2), respectively. Importantly, the CPM2 models, which exhibited the smallest discrepancy in average total releases from the BB and SK Dams, demonstrated a strong long–term quantitative agreement with the current operation. Moreover, the CPM1 models demonstrated a significant advantage over these optimization models in view of increasing the long–term end–of–wet season storage levels of two main storage dams, achieving + 15.73% (BB) and + 16.36% (SK). By comparison, the Fmincon model increased water storage by + 12.48% (BB) and + 5.23% (SK) (Kyaw et al. 2022), and the ANFIS model achieved + 6.94% (BB) and + 1.62% (SK) (Kyaw et al. 2024), while the DRL model targeted storage increase of approximately + 15% for both BB and SK Dams (Phankamolsil et al. 2025). This assures the crucial role of CP models in multiple reservoir operation and their ability to significantly enhance water scarcity resilience in the CPYRB due to increased water availability in major reservoirs.

The superior performances of CP models relative to DRL, NLP (specifically Fmincon), and ANFIS can be attributed to several structural advantages inherent in the CP formulation. First, the key hydrological and operational rules governing multi–reservoir operation in the CPYRB are explicitly encoded as constraints that any feasible solution must satisfy. These rules incorporate reservoir mass balance, storage limits, minimum ecological flow requirements, maximum safe channel capacities, side–flow utilization, flood threshold releases, and hydropower operating limits. Moreover, the multi–objective design of the models CPM1 and CPM2 aims to simultaneously minimize water deficits and excessive releases, maximize next–day storage, and minimize total releases over the planning horizon. This approach enables CP models to explore release trajectories that are both physically feasible and aligned with multiple system–wide performance criteria, rather than relying on penalty terms or post hoc rule adjustments to enforce constraints. Second, constraint propagation within the CP framework is crucial for eliminating infeasible or undesirable release patterns early in the search process. Because the constraints are applied jointly across time, reservoirs, and demand nodes, any proposed change in releases that could violate flood thresholds, deplete storage below minimum levels, or fail to meet time–shifted demands is rejected promptly. This mechanism reduces the effective search space and guides the solver toward release policies that balance water–supply reliability, storage preservation, and flood–risk reduction. In contrast, DRL and ANFIS learn release policies from historical or simulated data, which may not ensure strict satisfaction of constraints in all scenarios, especially during extreme inflow conditions. Furthermore, classical NLP approaches like Fmincon typically require meticulous tuning of penalty weights and initial guesses to manage a large number of complex, interacting constraints.

From a computational perspective, the CP–based formulations offer significant improvements while maintaining acceptable runtimes for long–term, daily–scale optimization. For example, on a MacBook Pro 2020 (with a 2.0 GHz Quad–Core Intel Core i5, 16 GB RAM, and running macOS 12 Monterey), solving the complete horizon across the entire dataset (approximately 20 years) takes about 4 h for both CPM1 and CPM2. However, in practical applications, models are typically run over a shorter rolling horizon (e.g., 30 days), which greatly reduces computational time and makes the approach suitable for near–real–time decision support. This reduction in computation time is substantial compared to the long–term retrospective simulations conducted here, indicating that the CP–based formulations are computationally feasible for practical decision–making applications while still strictly adhering to all hydrological and operational constraints. In contrast to alternative methods that require repeated training episodes (as seen in DRL) or extensive hyperparameter tuning (as in ANFIS), CP models offer a deterministic and reproducible framework. This allows for explicit control over constraint satisfaction, computational effort, and multi–objective trade–offs.

Limitations and future work

The CP models developed in this study rely on several assumptions regarding system inputs and dynamics. The optimization process and its modelling require a range of reservoir inputs: water balance–based data for all reservoirs, spatially distributed demands estimated for both local and joint demand points, and downstream potential side flow measured at key gauged stations. The daily reservoir optimization models with and without travel time delays were developed to consider flow dynamics in the river–reservoir system. However, capturing sub–daily flow dynamics in the CP models to describe the actual flow dynamics could not be possible since the system inputs were collected and estimated on the daily basis only. It is revealed that annual patterns of end–of–wet–season storages from the CPM2 model for all reservoirs, particularly at the KNB and PS Dams, deviated distinctly from those obtained from the CPM1 model and observed data. This result emphasizes that a delayed release of water from a dam due to travel time is one of the reasons significantly influencing the daily release scheme and storage changes among all reservoirs in the system. Since reservoir inflow, water demand, and potential side flow are key state variables that dictate the release determination and impact the performance of multiple reservoir operation system by CP models. Historical and future reservoir inflows are the primary driver of changes in water storage that represents water availability in reservoir system. Meanwhile, water demand determines the required release to be supplied from dams. Downstream side flow is also considered as key variable to reduce amount of dam release when it is potentially enough to meet the target demand. In other words, CP modelling is sensitive to these state variables, which directly impact reservoir storage changes and reservoir release schemes. Therefore, future research should focus on incorporating hydrological forecasts specifically reservoir inflow and downstream side flow from tributaries alongside water demand projections in all water sectors as input variables within the CP model to robustly support forecast–informed operations. Furthermore, to rationalize water supply particularly during the dry season, adjusting the delivery percentage based on available reservoir storage within the CP models is recommended. This aligns with hedging policy principles designed to uniformly distribute anticipated deficits over time, thereby moderating the peak severity of droughts and extending water availability for later use. These improvements would enhance the models' adaptability for real–time operation particularly during extreme flood and drought events and foster more resilient strategies under dynamic hydrological conditions.

Conclusion

This study developed two types of constraint programming models with and without incorporating travel time (CPM1 and CPM2) for multiple reservoir optimization in CPYRB. Formulating Constraint Optimization Problems (COPs) by constraint programming in CPYRB was based on the multi–objective multi–reservoir system operation and complex physical system constraints. The results showed the capability of the CPM1 and CPM2 models to increase the end–of–wet–season storages in reservoirs to potentially supply over dry season revealing enhanced water scarcity resilience in the basin. Moreover, the CPM1 and CPM2 models suggested maintaining proper available water storage levels to balance both water scarcity and flood moderation, resulting from the changes in release schemes among reservoirs in the system. Moreover, CPM2 provided realistic and effective guidelines for reservoir operational practice as enhanced water scarcity and flooding resiliencies were found due to the increased water availability particularly in normal and critical dry years and depleted reservoir storages in critical wet years. The key strength of constraint programming is that models developed using Python GEKKO optimization suite and IPOPT solver, a modern constraint programming language, can successfully solve large–scale problems with high speed and efficiency. Furthermore, CP models can incorporate solid multiple objectives and numerous system constraints in complex reservoir systems, which enhances the reliability of their results and helps achieve the desired goal of reservoir operation and management. However, the primary limitation of the developed CP models is their inability to adapt dynamically during the optimization process. Once the optimization begins, the model's structure, including objectives, decision variables, and system constraints, remains fixed. As a result, these models cannot incorporate new or evolving system conditions, such as sudden changes in inflow, updated demand forecasts, or revised operational rules, without re–solving the entire optimization problem. This limitation hinders the models' responsiveness to real–time or rapidly changing hydrological and operational conditions. Although CPM1 and CPM2 effectively generate optimal release and storage strategies under predetermined scenarios, their static nature restricts their application in adaptive, real–time reservoir operation where dynamic re–optimization is necessary.

Acknowledgements This research was funded by the Office of the National Research Council of Thailand (NRCT). The authors are grateful to the Royal Irrigation Department (RID), Electricity Generating Authority of Thailand (EGAT) for providing research data.

Author contributions All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by………. The first draft of the manuscript was written and reviewed by ………. and ………. and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Funding Open access funding provided by Mahidol University. This work was financially supported by the National Research Council of Thailand (NRCT), grant numbers SIP6230022. ………. received research support from NRCT in 2021.

Data availability The data is available upon request from the corresponding author.

Declarations

Conflict of interests The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Consent to participate The authors declare that they are aware and consent their participation in this paper.

Consent to publish The authors declare that they consent the publication of this paper

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

Informed consent For this type of study, formal consent is not required.

References

Akbarifard S, Sharif MR, Qaderi K (2020) Data on optimization of the Karun–4 hydropower reservoir operation using evolutionary algorithms. Data Br 29:105048

Ayele WT, Tenagashaw DY, Belew AZ, Andualem TG (2022) Optimal water allocation under climate change, based on stochastic dynamic programming model approach in Ribb Reservoir, Amhara, Ethiopia. Water Conserv Sci Eng 7:33–44. https://doi.org/10.1007/s41101-021-00125-w

Bai T, Wu L, Chang JX, Huang Q (2015) Multi–objective optimal operation model of cascade reservoirs and its application on water and sediment regulation. Water Resour Manage 29:2751–2770. https://doi.org/10.1007/s11269-015-0968-0

Bartàk R (2001) Theory and practice of constraint propagation. In Proceedings of the 3rd workshop on constraint programming in decision and control, pp. 7–14.

Beal LDR, Hill DC, Martin RA, Hedengren JD (2018) GEKKO optimization suite. Processes 6(8):106. https://doi.org/10.3390/pr6080106

Bessiere C, Quinqueton J, Raymond G (2006) Mining historical data to build constraint viewpoints. In Proceedings CP'06 Workshop on Modelling and Reformulation, pp. 1–16.

Cervellera C, Chen VCP, Wen A (2015) Optimization of a large–scale water reservoir network by stochastic dynamic programming with efficient state space discretization. Eur J Oper Res 171:1139–1151. https://doi.org/10.1016/j.ejor.2005.01.022

Charoenlerkthawin W, Namsai M, Bidorn K, Rukvichai C, Panneerselvam B, Bidorn B (2021) Effects of dam construction in the Wang River on sediment regimes in the Chao Phraya River Basin. Water. https://doi.org/10.3390/w13162146

Chen HT, Wang WC, Chen XN, Qiu L (2020) Multi–objective reservoir operation using particle swarm optimization with adaptive random inertia weights. Water Science and Engineering 13(2). https://doi.org/10.1016/j.wse.2020.06.005

Choudhari SA, Raj A (2023) Optimization of reservoir system operation using fuzzy set theory. International Journal of Civil Engineering. https://doi.org/10.14445/23488352/ijce-v10i6p105

Dabas P, Cooner V (2014) A review of constraint programming. Int J Comput Appl Technol Res 3(7):395–399

Faris MR, Ibrahim HM, Abdulrahman KZ, Othman LS, Marc KD (2021) Fuzzy logic model for optimal operation of Darbandikhan reservoir, Iraq. IIETA 16:335–343

Feng Z, Liu S, Niu W, Li S, Wu H, Wang J (2020) Ecological operation of cascade hydropower reservoirs by elite–guide gravitational search algorithm with Lévy flight local search and mutation. J Hydrol 581:124425. https://doi.org/10.1016/j.jhydrol.2019.124425

Freuder EC, Mackworth AK (2006) Chapte 2–onstraint Satisfaction: An Emerging Paradigm. Found Artif Intel. https://doi.org/10.1016/S1574-6526(06)80006-4

Giuliani M, Galelli S, Soncini-Sessa R (2014) A dimensionality reduction approach for many-objective Markov Decision Pro–cesses: application to a water reservoir operation problem. Environ Model Softw 57:101–114. https://doi.org/10.1016/j.envsoft.2014.02.011

Giuliani M, Lamontagne JR, Reed PM, Castelletti A (2021) A state–of–the–art review of optimal reservoir control for managing conflicting demands in a changing world. Water Resour Res 57(12):1–26. https://doi.org/10.1029/2021WR029927

He J, Tang Y, Guo X, Chen H, Guo W (2024) Research on hybrid reservoir scheduling optimization based on improved walrus optimization algorithm with coupling adaptive ε constraint and multi–strategy optimization. Sci Rep 14(1):11981. https://doi.org/10.1038/s41598-024-62722-8

Hentenryck PV (2024) Constraint programming. Rev Ouverte Intell Artif 5(2–3):139–159. https://doi.org/10.5802/roia.76

Hentenryck PV, Hoeve WV (2023) Constraint programming. Encyclopedia of optimization. 1–16.

Kraisangka J, Rittima A, Sawangphol W, Phankamolsil Y, Tabucanon AS, Talaluxmana Y, Vudhivanich V (2022) Application of machine learning in daily reservoir inflow prediction of the Bhumibol Dam, Thailand. 19th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI–CON), Prachuap Khiri Khan, Thailand 2022, pp. 1–4, https://doi.org/10.1109/ECTI-CON54298.2022.9795552

Kyaw KM, Rittima A, Phankamolsil Y, Tabucanon AS, Sawangphol W, Kraisangka J, Talaluxmana Y, Vudhivanich V (2022) Optimization–based solution for reducing water scarcity in the Greater Chao Phraya River Basin, Thailand: through re–operating the Bhumibol and Sirikit reservoirs using non–linear programming solver. Eng J 26(1).

Kyaw KM, Rittima A, Phankamolsil Y, Tabucanon AS, Sawangphol W, Kraisangka J, Talaluxmana Y, Vudhivanich V (2024) 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. App Envi Res. https://doi.org/10.35762/AER.2024009

Lai V, Huang YF, Kool CH, Ahmed AN, Sherif M, El-Shafe A (2023) Optimal water supply reservoir operation by leveraging the meta-heuristic Harris Hawks algorithms and opposite based learning technique. Sci Rep 13(1):6966. https://doi.org/10.1038/s41598-023-33801-z

Leite AR, Enembreck F, Barthès JPA (2014) Distributed constraint optimization problems: review and perspectives. Expert Syst Appl 41(11):5139–5157

Li S, Chen H, Wang M, Heidari AA, Mirjalili S (2020) Slime mould algorithm: a new method for stochastic optimization. Fut Gen Comput Syst 111:300–323. https://doi.org/10.1016/j.future.2020.03.055

Liu Y (2021) Construction and application of reservoir food control operation rules using the decision tree algorithm. Water 13:1. https://doi.org/10.3390/w13243654

Mezenner N, Dechemi N, Bermad A, Benkaci T (2024) Optimized reservoir operation using genetic algorithm and simulated inflows to reservoir based principal components analysis: case of Cheffia reservoir–Algeria. Model Earth Syst Environ 10(1):1–9. https://doi.org/10.1007/s40808-023-01779-2

Nethercote N, Stuckey PJ, Becket R et al (2007) MiniZinc: towards a standard CP modelling language. In: Bessiere C (ed) Principles and practice of constraint programming. Springer, Berlin, pp 529–543. https://doi.org/10.1007/978-3-540-74970-738

Niu W, Feng Z, Liu S, Chen Y, Xu Y, Zhang J (2021) Multiple hydropower reservoirs operation by hyperbolic Grey Wolf Optimizer based on elitism selection and adaptive mutation. Water Resour Manag 35:573–591. https://doi.org/10.1007/s11269-020-02737-8

Pawar S, Patel P, Mirajkar AB (2023) Multiobjective intuitionistic fuzzy optimization approach in optimal irrigation planning and operation of reservoir. Water Resour Manage 37:1033–1053. https://doi.org/10.1007/s11269-022-03406-8

Phankamolsil Y, Rittima A, Sawangphol W, Kraisangka J, Tabucanon AS, Talaluxmana Y, Vudhivanich V (2024) Fuzzy rule–based control of multireservoir operation system for flood and drought mitigation in the Upper Mun River Basin. Model Earth Syst Environ 10:5605–5619. https://doi.org/10.1007/s40808-024-02081-5

Phankamolsil Y, Rittima A, Sawangphol W, Kraisangka J, Tabucanon AS, Talaluxmana Y, Vudhivanich V (2025) Deep reinforcement learning for multiple reservoir operation planning in the Chao Phraya River Basin. Model Earth Syst Environ 11:102. https://doi.org/10.1007/s40808-024-02265-z

Rossi F, Van Beek P, Walsh T (2006) Handbook of constraint programming. Francesca Rossi, Peter van Beek, Toby Walsh. Elsevier.

Sawangphol W, Kraisangka J, Rittima A, Phankamolsil Y, Tabucanon AS, Talaluxmana Y, Vudhivanich V (2024) Constraint programming for reservoir operation optimization of Bhumibol Dam. Appl Water Sci 14(6):142. https://doi.org/10.1007/s13201-024-02179-2

Senlin C, Dan LI, Xiangming T, Yuhao H (2017) Development and application of a compensative regulation linear programming model for reservoir food–control. Adv Water Sci 28:507–514. https://doi.org/10.1442/j.cnki.32.1309.2017.04.004

Shrestha BP, Duckstein L, Stakhiv EZ (1996) Fuzzy rule–based modeling of reservoir operation. J Water Resour Plann Manage 122:262–269. https://doi.org/10.1061/(ASCE)0733-9496

Sinha GK, Purwar AK (2024) Optimization models in water resources management and security: a critical review. Int J Math Eng Manag Sci 9(1):129–146. https://doi.org/10.33889/IJMEMS.2024.9.1.007

Teegavarapu RSV, Simonovic PS (2002) Optimal operation of reservoir systems using simulated annealing. Water Resour Manag 16(5):401–428. https://doi.org/10.1023/A:1021993222371

Tsitsiklis J, Van Roy B (1996) Feature–based methods for large scale dynamic programming. Mach Learn 22(1–3):59–94. https://doi.org/10.1007/978-0-585-33656-5

Unver OI, Mays LW (1990) Model for real–time optimal food control operation of a reservoir system. Water Resour Manag 4:21–46. https://doi.org/10.1007/BF00429923

Wahyuni S, Sisinggih D, Elhuda I, Souma K, Dasylva IZ (2024) Optimization of reservoir release operation using genetic algorithm method. Results Eng 23(2024):102610. https://doi.org/10.1016/j.rineng.2024.102610

Wallace M (1995) Constraint programming. William Penney Laboratory, Imperial College, London SW7 2AZ

Wang CH, Blackmore JM (2009) Resilience concepts for water resource systems. J Water Resour Plan Manag 135(6):1–26. https://doi.org/10.1061/(ASCE)07339496

William WGY (1985) Reservoir management and operations models: a state–of–the–art review. Water Resour Res 1:1. https://doi.org/10.1029/WR021i012p01797

Yakowitz S (1982) Dynamic programming applications in water resources. Water Resour Res 18(4):673–696. https://doi.org/10.1029/WR018i004p00673

Zetai Y, Hao Z, Suzhen F, Cheng C, Jinwen W (2022) Optimal multi-reservoir operation for food control under constrained operational rules. J Flood Risk Manag 15:1. https://doi.org/10.1111/JFR3.12825

Authors and Affiliations

Wudhichart Sawangphol[1] · Areeya Rittima[2] · Yutthana Phankamolsil[3] · Jidapa Kraisangka[1] · Allan Sriratana Tabucanon[4] · Yutthana Talaluxmana[5] · Varawoot Vudhivanich[6]

✉ Areeya Rittima
areeya.rit@mahidol.ac.th

Wudhichart Sawangphol
wudhichart.saw@mahidol.ac.th

Yutthana Phankamolsil
yutthana.pha@mahidol.ac.th

Jidapa Kraisangka
jidapa.kra@mahidol.ac.th

Allan Sriratana Tabucanon
allansriratana.tab@mahidol.ac.th

1 Faculty of Information and Communication Technology, Mahidol University, Phuttamonthon, Nakhon Pathom 73170, Thailand

2 Faculty of Engineering, Mahidol University, Phuttamonthon, Nakhon Pathom 73170, Thailand

3 Environmental Engineering and Disaster Management Program, Mahidol University, Kanchanaburi Campus, Thailand

4 Faculty of Environment and Resource Studies, Mahidol University, Phuttamonthon, Nakhon Pathom 73170, Thailand

5 Department of Water Resources Engineering, Faculty of Engineering, Kasetsart University, Bangkok, Thailand

6 Department of Irrigation Engineering, Faculty of Engineering at Kamphaeng Saen, Kasetsart University, Bangkok, Thailand