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Real-time Operation of a Multi-Reservoir System

Real-time Operation of a Multi-Reservoir System

Dissertation

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In memory of
Dr. ir. Peter-Jules van Overloop

SUMMARY

RESERVOIRS have a significant role to manage fresh water resources for irrigation, hydropower generation, domestic and industrial use, flood and drought control and navigation. To date, more than 50,000 large dams have been constructed in the world for providing water-related services to our society that support socioeconomic development of many regions. An efficient reservoir operation helps us to maximize benefits and to minimize the negative impacts of existing reservoirs. In practice, reservoir operation is a complex decision-making process involving multi-variables, multiple objectives and constraints, nonlinearity, and uncertainty. A framework of reservoir operation typically involves optimization and simulation procedures in which releases of reservoirs are determined by optimizing the objective functions and the system performance is evaluated using a simulation model. Despite significant developments in reservoir operation have been made in the last 50 years, there is a little progress for operation of a multi-reservoir system concerning real-time control, multi-objective optimization and a basin-wide approach. Therefore, Chapter 2 presents optimization and simulation methods developed in the recent literature and the potential of model predictive control (MPC) for real-time reservoir operation.

Water demand is being increased everywhere due to population growth, urbanization and food security. Thus, it may be required to improve operating rules of existing reservoirs to adopt changing needs of the future. As science and technology developed, advanced control methods are available to operate complex water systems, especially when the controlled water systems have low performance using the conventional control methods such as feedback control, feedforward control and a combination of feedback and feedforward control. MPC is a promising method to operate a reservoir system because its ability to deal with multi-variables, constraints, system dynamics and uncertainty. Another advantage is that the control actions are calculated based on the current and future states of the system. However, a standard MPC approach needs to be extended for real-time operation of a large-scale reservoir system addressing the computational burden and a search technique for compromised solutions between the conflicting objectives. Based on this gap, a research question of this thesis is:
"Can MPC be used to meet the operational objectives of a multi-reservoir system?"
A reservoir system is generally composed of reservoirs, hydraulic structures and river reaches and, the system dynamics are nonlinear in nature. It is important to capture the dynamics of such system for finding relevant control actions. The Saint-Venant equations can be used to simulate the water levels and flows of a water system. In order to reduce the computational time, these partial differential equations were discretized in time and space using a large-grid size and a large-time step discretization scheme. This system model was calibrated and validated using the observed data. This simplified model is able to capture the relevant system dynamics and reasonable to used for real-time operation of a reservoir system. The detailed modelling procedures are dis-

cussed in Chapter 2 and 3.

In Chapter 4, an MPC controller was developed for a large-scale reservoir system in which a simplified internal model was used to predict the current and future states of the system. A real-world case study was conducted for flood mitigation at a downstream area by controlling the water levels of reservoirs and a river reach. The results show a clear improvement in flood risk reduction using MPC compared to the current operation of existing reservoirs. A constraint method was adopted to solve the conflicts between objectives, for example, flood control and hydropower production. The optimization problem was solved by the interior point method implemented in MATLAB program. The control actions could be calculated in a few seconds that makes it suitable for real-time implementation.

Most reservoir operation problems deal with more than one objective function. These objectives are often conflicting one another in solving optimization problems. In the standard MPC formulation, a weighted-sum or a constraint method is usually used to find an optimal solution between multiple conflicting objectives. However, these methods are limited to finding all trade-off solutions so called the Pareto-optimal solutions in a single run. More flexible operation will be achieved if a decision-maker can visually check all Pareto- optimal solutions and the effect of a selected solution on each objective at every control step. This brings an extension of the standard MPC to multi-objective MPC (MOMPC) in which a multi-objective optimization problem is solved using non-dominated sorting genetic algorithm II and a multi-criteria decision-making method. The formulation and application of an MOMPC approach in an existing multi-reservoir system are presented in Chapter 5. The advantages of this approach are its ability to find all possible solutions and visual presentations of the trade-offs between multiple conflicting objectives. This helps the decision-makers to improve the performance of the controlled water system.

Finally, it is recommended that the proposed MOMPC method can be used as an alternative approach to operate the large-scale reservoir systems when the classical control methods are not able to provide a reasonable performance.

Samenvatting

Reservoirs spelen een essentiële rol bij het beheer van zoetwater voorraden voor huishoudelijk en industrieel gebruik, bij waterkracht centrales, controle over droogte (irrigatie) en overstromingen, en de navigatie van rivieren. Tot op heden, zijn er wereldwijd meer dan 50.000 grote dammen gebouwd om te voorzien in water gerelateerde diensten ten behoeve van sociaal-economische regionale en maatschappelijke ontwikkelingen. Een efficiënt functionerend reservoir is optimaal om voordelen te optimaliseren en nadelen te minimaliseren. De operatie van een reservoir is een complex proces van besluitvorming met betrekking tot diverse variabelen, doelstellingen, beperkingen, nonlineariteit en onzekerheid. De reservoir procedures behelsen optimalisatie, simulatie en evaluatie van functies en prestaties van het systeem in een simulatie model, naar aanleiding waarvan het vrijkomen van reservoir water wordt bepaald. Ondanks de ontwikkelingen op het gebied van reservoirs gedurende de afgelopen 50 jaar, is er minder vooruitgang geboekt met betrekking tot de “real-time” controle, de multi-objectieve optimalisatie en een bekkenwijde benadering in de operatie van multipele reservoirsystemen. Daarom worden in Hoofdstuk 2 de recente optimalisatie- en simulatie methodes besproken, en vervolgens het potentieel van een “real-time” operatie, de zgn. “Model Predictive Control” (MPC), voor reservoirs gepresenteerd.

De vraag naar water neemt toe als gevolg van bevolkingsgroei, verstedelijking en de zekerheid om in voeding te voorzien. Het is dus van essentiëel belang om de exploitatie van de reeds bestaande reservoirs aan te passen aan de veranderende behoeften van de toekomst. Naarmate de wetenschap en technologie zich ontwikkelen, komen ook geavanceerde controlemethodes beschikbaar om complexe watersystemen te beheren; met name de watersystemen die als gevolg van conventionele besturing, zoals “feedback“, “feedforward”, of een combinatie van “feedback/feedforward” controle, minder goed functioneren. MPC is, in het geval van reservoir beheer, een veelbelovende methode om multi-variabelen, beperkingen en onzekerheden, en de dynamiek van een systeem te bevatten. Een voordeel is ook dat de controles op basis van zowel de huidige als de toekomstige toestand van het systeem worden berekend. Echter, een standaard benadering van MPC is ontoereikend voor het beheer van een grootschalig systeem van reservoirs, waarvoor een “real-time” benadering noodzakelijk is. Aanpassing van MPC met computionele zoektechnieken en rekencapaciteit is nodig om de tegenstrijdige doestellingen en gecompromiteerde oplossingen te adresseren. De onderzoeksvraag voor deze dissertatie, gebaseerd op dit verschil, luidt aldus:

"Kan MPC worden gebruikt om te voldoen aan de operationele doelstellingen van een systeem met meerdere reservoirs?"

Een reservoir-systeem is over het algemeen samengesteld uit meerdere reservoirs, hydraulische structuren en rivieren; kortom, een dynamisch systeem wat van nature niet

lineair is. Het is daarom belangrijk om de dynamiek van een dergelijk systeem vast te leggen en de relevante controle punten te vinden. In deze studie zijn de “De-Saint-Venant” vergelijkingen gebruikt om waterstanden en -stromingen van een watersysteem te simuleren. Om de rekentijd te verminderen, werden deze partiële-differentiaal vergelijkingen in tijd en ruimte gediscretiseerd dmv een schema met grote tijdstap en groot raster. Dit model werd gekalibreerd en gevalideerd m.b.v. geobserveerde gegevens. Dit vereenvoudigde model is in staat om de relevante systeemdynamiek vast te leggen en geeft een bevredigend resultaat om te worden gebruikt in een “real-time” toepassing voor een systeem van reservoirs. De gedetailleerde modelleringsprocedures worden in Hoofdstuk 2 en 3 nader besproken.

In Hoofstuk 4 wordt de ontwikkeling besproken van een “MPC-controller” voor een grootschalig reservoirsysteem, waarin een vereenvoudigd intern model werd gebruikt om de huidige en toekomstige toestand van het systeem te voorspellen. Een case study werd uitgevoerd om, door controle van waterstanden van reservoirs en riviertoegang tot reservoirs, overstroming bij een stroomafwaarts gebied te beperken. Deze resultaten lieten een duidelijke verbetering zien in een verminderde kans op overstroming bij het gebruik van MPC in vergelijking met de huidige operatie van de bestaande reservoirs. Een beperkende methode werd geadopteerd om de conflicten tussen de diverse doelstellingen op te lossen; bijvoorbeeld, beperking van overstroming en productie van waterkracht-energie. Het probleem van optimalisatie werd opgelost door de in het MATLAB-programma geïmplementeerde “binnenpunt” methode. De besturingsacties kunnen in enkele seconden worden berekend, waardoor deze method bij uitstek geschikt is voor “real-time” implementatie. De meeste problemen m.b.t. reservoir operatie hebben te maken met meer dan één objectieve functie. Deze objectieve doelstellingen zijn vaak tegenstrijdig en problematiseren de op te lossen optimalisering. In de standaard MPC-formulering wordt meestal de methode van een gewogen som of restrictie gebruikt om tussen meerdere conflicterende doelstellingen een optimale oplossing te vinden. Deze methoden zijn echter beperkt tot het vinden van alle afwegende oplossingen, de zgn optimale “Pareto” oplossingen, in een enkele ronde. Een flexibelere operatie zal worden bereikt als alle Pareto-optimale oplossingen en het effect van de geselecteerde oplossing op iedere doelstelling en elke controle stap visueel gecontroleerd kan worden. Dit resulteert in een uitbreiding van de standaard MPC naar een “Multi-Objective MPC” (MOMPC), waar een multi-objectief optimalisatie problem wordt opgelost m.b.v. het niet-dominant, sorterend genetisch algoritme II en een besluitvormingsmethode met multipele criteria. De formulering en toepassing van de MOMPC aanpak in een bestaand systeem met meerdere reservoirs wordt in Hoofdstuk 5 gepresenteerd. Het voordeel van deze benadering is het vermogen om alle mogelijke oplossingen te vinden en de visuele presentatie van de overwegingen tussen meerdere en tegenstrijdige doelstellingen te zien. Dit maakt het mogelijk voor bestuurders om verbeteringen aan te brengen in de prestaties van gecontrolleerde watersystemen.

Ten slotte wordt de voorgestelde MoMPC method aanbevolen als een alternatieve aanpak in de operatie van een grootschalig systeem van meerdere reservoirs, in het geval dat de klassieke besturingsmethodes niet voldoende prestaties kunnen leveren.

CONTENTS

1

INTRODUCTION

Water is essential in human life and the proper management of water resources benefits to our societies. This chapter introduces the role of dams in water resources management, real-time operation and the facing challenges.

1

1.1. DAMS IN WATER RESOURCES MANAGEMENT

Water is essential in human life. The proper management of water resources benefits to our societies. Over the past centuries, water infrastructure such as dams, dikes, barrages, weirs, pumps, sluice gates and other hydraulic structures has been constructed worldwide to manage water resources. Dams (or) reservoirs are built across rivers or streams to store water for irrigation, hydropower generation, flood management, domestic and industrial water supply, navigation and other environmental related purposes and they are used for either single or multiple purposes. According to the International Commission On Large Dams (ICOLD) (https://www.icold-cigb.org/GB/dams/role_of_dams.asp), world's single purpose dams are mainly used 48% for irrigation, 17% for hydropower generation, 13% for water supply, 10% for flood control, 5% for recreation and less than 1% for navigation and fish farming. Worldwide, dams contribute to food security as about 250 million hectares of land are cultivated under irrigation (International Commission on Large Dams, 1987). In addition, dams also provide for the one-fifth of the world's electricity, as well as flood risk reduction, drinking water supply and river flow regulation [Altinbilek, 2002]. At present, about 50,000 dams have been built around the world [Lehner et al., 2011] and they clearly contribute to regional or national development.

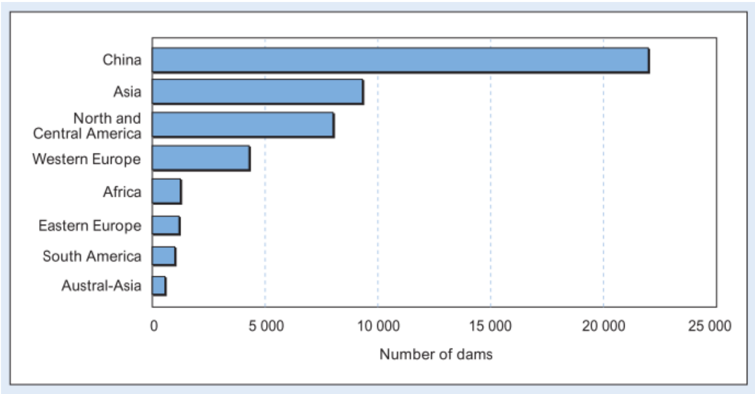

Figure 1.1: Regional distribution of large dams at the end of the 20th century. Source:[WCD, 2000]

As the negative consequences of large dams on people, river basins and ecosystems are becoming evident, the public debate on the development of large dams has been emerging between dam officials, affected people and environmental activists concerning various controversial issues, such as costs and benefits, environmental impacts and sustainability, social impacts and equity, economics and finance, governance and participation, accountability and alternative to dams. The report, "Dams and Development" published by the world commission on Dams (WCD) in 2000, addressed the development effectiveness and impacts of large dams in the global scale and presented a new framework for decision-making on water resources development [WCD, 2000]. The WCD states that "Dams have benefited the general public through their contribution to food production and increased access to electricity, along with providing other direct benefits and multiplier effects." On the other hand, considerable social and environmental issues exist through construction and long-life operation of large dams. These issues include physical transformations of rivers, degradation of watershed ecosystems and social impacts like displacement of people, changes in people's livelihoods and loss of cultural heritages [WCD, 2000]. In this context, Biswas and Tortajada [2010] reported the development of large dams over the world and pointed out the absence of overall impact analysis, including both positive and negative views in the available literature. Altinbilek [2002] discussed an overview on the role of dams in water resources management and highlighted the significant contribution of dams to Turkey's economy based on irrigation, hydropower generation and domestic and industrial water supply development. Like the other countries, dams play an important role in Myanmar's agriculture development and electric energy production. After the construction of 235 dams in the last four decades, irrigable area is extended up to 16.1 % of net sown area. This provides the opportunities to the farmers to grow a second crop in the dry season and improves their income and livelihoods. Myanmar has a great potential in hydropower generation and has currently developed 7 % of hydropower potential. At present, hydropower contributes 50 % in total electric power production. There are the eight ongoing projects with the installed capacity of 1691.6 MW and the new projects have been planned to produce about 41186 MW to meet the increasing demand in the future. According to the plan, it is required to construct new dams in Myanmar for further development through addressing the social and environmental impact.

The climate is changing all over the world and the world's population is growing continuously, which leads to increase water demands and related services. Ehsani et al. [2017] presented a future trend for the development of dams associated with climate change impacts. This regional study suggests that the role of dams will increase in the future to provide water and food security. In addition, operations of existing reservoirs need to be modified to deal with future climate uncertainties. Although approximately 60% of world's existing large dams are located in the developing countries [WCD, 2000] (see Figure 1.1) , it is necessary to construct new dams in these regions during the coming decades to meet the growing demands of water, food, and energy. To do this, the remaining controversial issues in the construction of large dams still need to be resolved by maximizing the social and environmental benefits and by minimizing the adverse impacts. The WCD suggests that "Restoring or extending the life of existing dams and, where feasible, expanding and improving services from existing dams provide major opportunities to address development needs [WCD, 2000]". Adopting developed technology and lessons learned from the past development, it is possible to improve the performance of many existing dams to meet the changing needs of the future.

1.2. Reservoir operation

Reservoirs store and regulate water for various purposes. Typically, a reservoir has two outlet structures called a spillway and a conduit (pipe). A controlled or uncontrolled spillway serves to spill any excess water during high inflow. A conduit is used to release water for irrigation, hydropower generation and domestic water supply, and to regulate downstream river flow for flood management, navigation and environmental conservation. Generally, a reservoir storage is divided into one or more zones to designate available storage capacities for multi-purpose uses (see Figure 1.2). The dead storage zone is defined based on design life of a reservoir to reserve for sedimentation from the upstream catchment. The conservation zone provides water for irrigation, domestic supply, electricity production and recreation. During the wet season, flood control storage is used to regulate the downstream river flow to reduce the flood risk. The surcharge zone provides a space for a high inflow exceeding above flood control zone and releases excess water through a spillway for dam safety. The design high flood level is defined through reservoir routing that usually uses 10,000 years return period flood for large dams. Reservoir operation is to decide how much water needs to be stored or released from a storage zone using the operating rules. In other ways, it is required to maintain the reservoir water level at or as closely as to the desired water level based on the inflow and the current storage volume. Therefore, reservoir release depends on the inflow, demand, current storage volume and capacities of the spillway and conduit. Reservoir operations depend on the inflow, demands, actual storage volumes and release capacities of spillway and conduit. During a flood event, reservoir releases also depend on the allowable flow rates of the downstream control point. Reservoir operations may be categorized as a short-term and a long-term operation. Short-term operation refers to real-time control based on hourly or daily time intervals and long-term operation refers to the planning and evaluation of long-term strategies based on seasonal or monthly time intervals. For all operations, it is required to decide how much water needs to be released and when it will be released to meet the operating objectives subject to operational constraints.

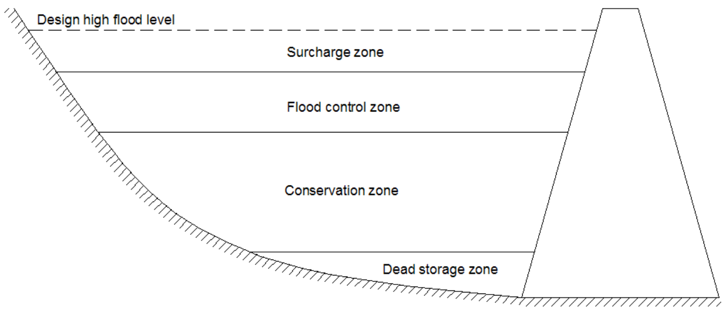

Figure 1.2: Reservoir storage zones

Reservoir operators may use the predefined rules (e.g., rule curves) to determine the release rates of reservoirs [Loucks et al., 2005; Taghian et al., 2014]. Typically, a rule curve is designed for a year based on the inflow, demand and reservoir losses. It represents the desired reservoir storage levels at each season or month. Using a rule curve, reservoir operator attempts to maintain the reservoir water levels as closely as possible to the desired water levels while supplying to meet various water demands. Generally, a rule curve does not change year by year. However, due to uncertain inflow and changing demands, it is often required to modify a rule curve for achieving desired storage levels, especially in drought periods. In addition to refining reservoir operation policies, the hedging rules were also developed to reduce water shortage in the future. This allows saving water for later use while accepting the deficits in the present water supply [You and Cai, 2008]. The use of predefined rule is simple in operation, however, sometimes inflexible to deal with inflow uncertainty and extreme situations. In Myanmar, an experience-oriented method is used to operate the reservoirs in which the operators decide to store or release water based on the present and future conditions (e.g., water level, rainfall and demand) and the past records (e.g., water level and rainfall). This method is more flexible to deal with uncertain inflow and changing demands compared to a pre-defined method. However, without optimizing operations, it is difficult to find the optimal releases for the dams used for multiple purposes such as flood management and hydropower generation. In the last decades, simulation or optimization method are used as the decision support tools in reservoir operations. Taghian et al. [2014] presented a method to couple the conventional rule curves with hedging rules for the minimization of drought effect in the Zohre river basin in which a simulation-optimization approach was used to improve the existing reservoir operating policy considering both normal and drought situations.

At present, various simulation and optimization methods are available as powerful tools for reservoir management and operation. Simulation models help us to analyze possible system performance over time under given operating policies [Johnson et al., 1991; Sigvaldson, 1976] On the other hand, mathematical optimization methods can be used to determine optimal releases of a reservoir or a reservoir system, subject to the system constraints [Chen et al., 2007; Crawley and Dandy, 1993; Mariño and Mohammadi, 1983]. The combined simulation-optimization approaches are also used to define reservoir operating rules in many studies [Che and Mays, 2015; Liu et al., 2011; Zatarain Salazar et al., 2017].

1.3. MULTI-RESERVOIR OPERATION

For a basin scale, a river basin may have more than one reservoir. In this case, a multi-reservoir operation is required to meet the water demand or flood control at the location where river flows are changed by releases from two or more reservoirs. In Figure 1.3, releases from the reservoir 2 and 3 contribute to flow changes at point A and releases from reservoir 1, 2 and 3 contribute to flow changes at point B. In this system, releases from all reservoirs need to be controlled for flood protection at point C. Reservoirs may be located in a series or parallel within a river basin. For reservoirs in series (e.g., Reservoir 2 and 3 in Figure 1.3), the simplest way to make a release decision is to meet the water demand by releasing lower storage capacity first and to minimize spill from the system by first filling the upper reservoir. For reservoirs in parallel (e.g., Reservoir 1, 3 and 4 in Figure 1.3), release decisions are determined based on balancing the storage capacities of reservoirs to minimize the water shortage and to avoid unnecessary spill from the system. A wide range of operating rules for reservoir in series or in parallel was presented by Lund and Guzman [1999]. However, they mainly focused on operating rules for a single purpose reservoir and suggested using simulation-optimization approaches for the operation of multi-reservoir systems involving multiple objectives.

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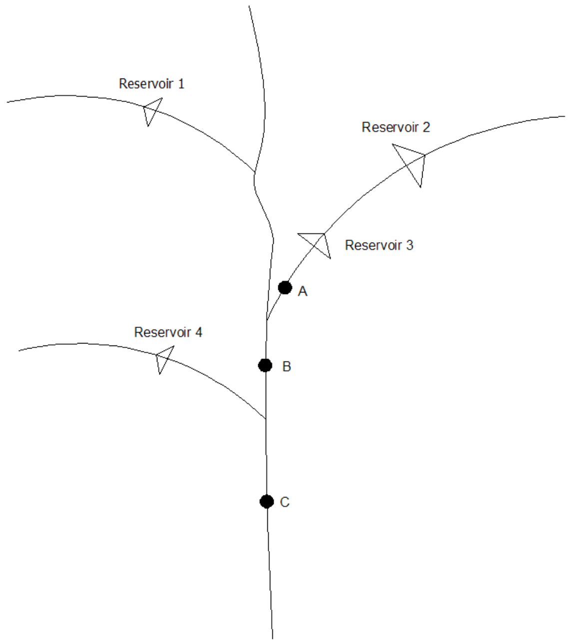

Figure 1.3: An example of Multi-reservoir system

For multi-reservoir operation, a complex decision-making process is required to deal with conflicting objectives, system constraints, non-linearity in the system dynamics and uncertainties associated with inflow, demands and losses [Castelletti et al., 2008; Oliveira and Loucks, 1997]. Over the past decades, many researchers emphasized to overcome these challenges by developing a wide range of optimization methods and simulation models [Fayaed et al., 2013]. For multi-objective optimization, linear programming (LP), dynamic programming (DP), non-linear programming (NLP) and evolutionary multi-objective optimization (EMO) are widely used to find releases of reservoirs by maximizing or minimizing objective functions subject to all system constraints. Simulation models also play important roles in reservoir management to evaluate the behavior of a reservoir system under specified conditions. Generally, a simulation model is based on a mass balance approach to approximate the movement of water along the upstream to the downstream reaches. A multi-reservoir system analysis usually requires a simulation model incorporating an optimization scheme to evaluate optimal operating policies for short or long-term operation. At the present, state-of-the-art reviews of developed reservoir system management and operation techniques can be found in [Fayaed et al., 2013; Labadie, 2004; Rani and Moreira, 2010; Yeh, 1985] and an overview of these techniques are discussed in the next chapter.

1.4. FACING THE CHALLENGES IN MULTI-RESERVOIR OPERATIONS

In this section, we highlight the main challenges facing in multi-reservoir operation problems. Operation of a multi-reservoir system involves many stochastic components, such as precipitation, evapotranspiration and inflow. In the system analysis, uncertainty associated with these components needs to be taken into account for a better performances of a controlled system. In general, most of the past studies focus on how to solve uncertain streamflow problems using stochastic linear programming (SLP) [Yeh, 1985] or stochastic dynamic programming (SDP) [Braga et al., 1991; Kelman et al., 1990; Li et al., 2014; Stedinger et al., 1984]. SLP is simple in its formulation but it is limited in handling non-linear problems and non-separable objective functions [Yeh, 1985]. The significant advantage of SDP is that it can deal with nonlinear and stochastic features involved in operations of multi-reservoir systems. However, this formulation allows a limited number of reservoirs to avoid an exponential growth of state variables, the so-called curse of dimensionality problem [Labadie, 2004]. Another approach to overcome uncertainty is using ensemble forecasts and ensembles of stochastic hydrological inputs. Zatarain Salazar et al. [2017] addressed uncertainty by using different-sized ensembles of synthetic stream flows and evaporation rates in many objective reservoir optimization. Ensemble forecast data involve a set of data which presents a range of possible future states of the atmosphere. Recent studies discussed the use of ensemble forecasts in optimal operations of reservoirs under forecast uncertainty [Anvari et al., 2014; Raso et al., 2014; Schwanenberg et al., 2015; Uysal et al., 2018].

Multi-reservoir operations involve multiple objectives that may conflict with one another in the decision-making process, challenging the decision-makers to take optimal release decisions. Typically, multi-objective optimization methods are used to find trade-off optimal solutions between multiple conflicting objectives. A simple way to deal with a multi-objective optimization problem (MOP) is using the weighted-sum approach in which each objective is multiplied by an assigned weight factor,subsequently,all weighted objectives are summed up to form a single objective optimization problem [Zadeh, 1963]. A choice of weight factor is based on the relative importance of each objective, consequently, a solution obtained by this approach is sensitive to the chosen weight factors [Deb, 2014]. In addition, the weighted-sum method is subjective to analyze trade-off solutions of a MOP by using different set of weight factors. The ϵ-constraint method introduced by Haimes et al. [1971] is also applicable to obtain the optimal solutions in a multi-objective analysis. In this approach, efficient solutions can be found by optimizing one of the objectives, while the other objectives are treated as constraints. Yeh and Becker [Yeh and Becker, 1982] applied a combined LP-DP method to determine the optimal releases of reservoirs for minimizing the stored potential energy losses subject to the four other objectives as constraints. A successful application of the constraint method to multi-reservoir operation could be found in the work by Mohan and Raipure [1992] who developed a multi-objective linear programming model for the maximization of irrigation supply and hydropower production under a set of constraints. The drawbacks of this method are that the solutions mainly depend on defined constraints and it is required to solve the model many times to obtain trade-off solutions when many lower bound constrains exit [Deb, 2014; Loucks et al., 2005]. In a MOP, it is possible to have a number of optimal solutions when conflicting objectives are solved. The classical approaches such as the weighted-sum or the constraint method based on LP, DP and NLP are not able to provide all optimal solutions in a single run. Thus, the use of multi-objective evolutionary algorithms (MOEA) has emerged during the last three decades to address MOPs in the planning and management of water resources [Nicklow et al., 2010; Reed et al., 2013]. Evolutionary algorithms (EA) are metaheuristic optimization algorithms based on the biological evolution processes such as regeneration, crossover, mutation and selection. The popularity of EA is its ability to find the Pareto optimal solutions. This offers the decision makers to select the most suitable alternative based on their preferences. Moreover, MOEAs can be used to deal with non-linearity, non-convexity and discontinuous problems which are attractive for multi-objective optimization. Recent studies prove that EAs are applicable for various multi-reservoir operations such as a framework to evaluate the impact of problem formulations on the system performance [Quinn et al., 2017], optimal strategies involving ecological sustainability requirements for multipurpose reservoir operation [Chang et al., 2010], minimizing reservoir releases and maximizing energy production [Reddy and Kumar, 2006], joint operation of a reservoir and a diversion weir [Yin and Yang, 2011], a diagnostic assessment of parallel strategies for many objective reservoir optimization [Zatarain Salazar et al., 2017] and improvement strategies for cascade reservoirs optimization [Yang et al., 2013]. However, every reservoir system has its own characteristics which influence on problem formulation and optimization and poses the difficulty to use the existing algorithms for any reservoir system. Therefore, it is still needed to explore a broader use of EAs in the field of multi-reservoir operation dealing with strong uncertainties, robust optimization, multi-criteria decision making and real-time operation [Adeyemo and Stretch, 2018; Nicklow et al., 2010].

Only the most recent studies focus on long-term performance of reservoir operation strategies developing various simulation and optimization models. Consequently, there is a limited availability of real-time operation studies in the past, especially for multi-reservoir operation under multiple objectives. The main reasons the problem of computational efficiency related to the curse of dimensionality by using dynamic programming and the difficulty of finding optimal solutions using the classical methods. Several real world case studies aim at solving real-time reservoir operations and how to overcome issues related to curse of dimensionality and inflow uncertainty involving one to five reservoirs. Significant studies are, for example,multi-reservoir operation using a combined LP-DP approach [Becker and Yeh, 1974], daily reservoir operation using linear quadratic gaussian control [Wasimi and Kitanidis, 1983], flood control with three reservoir using LP [Needham et al., 2000], real-time flood control based on optimal tree-based release rules using a mixed-integer linear programming for flood control optimization and the feed-forward back-propagation neural network for river channel routing [Wei and Hsu, 2009], daily optimal operation of cascade reservoirs using adaptive genetic algorithm [Yang et al., 2013], short-term reservoir operation using tree-based model predictive control (TB-MPC) [Raso et al., 2014], reservoir optimization for flood mitigation using ensemble forecasts in combination with the multi-stage stochastic optimization [Schwanenberg et al., 2015] and hourly flood control operation of hydropower reservoir using Multi-Stage Stochastic TB-MPC [Uysal et al., 2018]. However, further investigation is required to focus on multi-objective analyses of real-time multi-reservoir operation to evaluate trade-offs between multiple conflicting objectives. Many authors suggest that a simulation-optimization framework is an effective approach for solving complex reservoir operation problems [Liu et al., 2011; Rani and Moreira, 2010; Wei and Hsu, 2008;

Zatarain Salazar et al., 2017]. Among the available methods, the structure of model predictive control (MPC) is based on the simulation-optimization approach and MPC has a high potential for addressing real-time operation of multi-reservoir systems with multiple control objectives [Breckpot et al., 2013; Ficchì et al., 2016; Galelli et al., 2014].

1.5. MULTI-RESERVOIR OPERATION USING MODEL PREDICTIVE CONTROL

Model Predictive Control (MPC), a model-based control technique, has appeared in the process control industry since late 1970s [García et al., 1989]. As a method for predictive control, MPC has an ability to deal with a complex system composed of multiple variables, non-linearity, uncertainties and constraints [Mayne, 2014]. In fact, it has been widely applied in operational water management to control irrigation systems [van Overloop, 2006b; van Overloop et al., 2010; Sadowska et al., 2014; Zafra-Cabeza et al., 2011], drainage systems [Abou Rjeily et al., 2018; Gelormino and Ricker, 1994; Maestre et al., 2013; van Overloop et al., 2008]and reservoir operations [Breckpot et al., 2013; Delgoda et al., 2013; Tian et al., 2017]. MPC is an online control approach that uses a process model or an internal model to predict future system behavior and an optimization algorithm is defined to find optimal control inputs over a finite prediction horizon. In MPC formulation, control inputs are determined along a prediction horizon for every time step, where first control input is implemented to move to the next step, the so called the receding horizon control. In this way, MPC provides the predictive solutions for real-time control (RTC) problems. The structure diagram of MPC is shown in Figure 1.4.

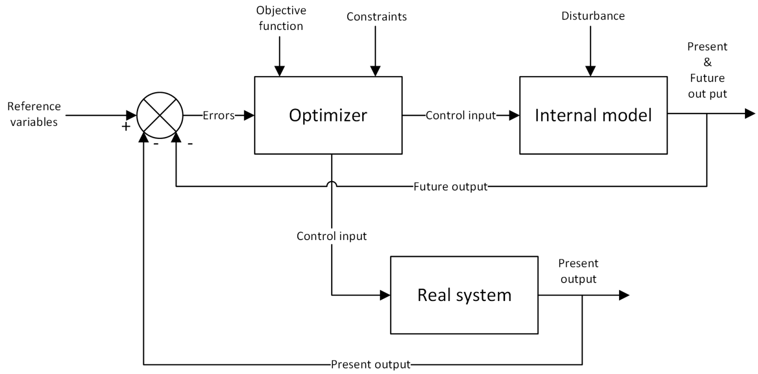

Figure 1.4: Structure diagram of Model Predictive Control

In MPC, an internal model is formulated as linear or non-linear model based on nature of the system. Generally, a reservoir system is composed of rivers, reservoirs and hydraulic structures that have non-linear natures. The dynamics of open channel flow is usually modelled by using De Saint Venant equations and the integrator delay (ID) model [Zhuan and Xia, 2007], because a detailed modelling of non-linearity is computationally expensive to use for RTC problems [Xu, 2013]. The ID model developed by Schuurmans[Schuurmans et al., 1995] is not able to account for all relevant system dynamics that given parameters (i.e. delay time and storage area) work for only one control point and, thus, it is unsuitable to use for river systems. van Overloop [2006b] suggests to use a simplified model based on discretized the De Saint Venant equations which are able to capture the dynamics of river system from a low to high flow. Xu [2013] applied the staggered conservative scheme (developed by [Stelling and Duinmeijer, 2003] to discretize the De Saint Venant equations for RTC of combined quantity and quality in open Channels. An advantage of this method is that it can be used for any Froude numbers. Tian et al. [2015] also shows the applicability of this method to control a large scale water system using with a large grid size and a large time step. In this thesis, we employ this method to control multi-reservoir systems.

In MPC formulation, quadratic programming (QP) is often used to optimize a cost function over a finite horizon subject to linear constraints [Bemporad et al., 2000; Rao et al., 1998]. For multi-objective optimization, a classical approach, such as a weighted-sum or a constraint method, is usually applied to find an optimal solution [Galelli et al., 2014; Uysal et al., 2018]. However, these methods are limited to search all Pareto optimal solutions for multiple conflicting objectives in a single run. Therefore, there is increased focus to use MOEA in operational water management, because it is able to provide the Pareto optimal solutions and thus enabling more flexibility in the selection of a preferred alternative. MOEA is a population-based optimization algorithm and recent studies have shown successful applications of MOEA in MPC formulation to solve various RTC problems (e.g. [Chiang and Willems, 2015; Malekmohammadi et al., 2011; Vermuyten et al., 2018]). However, a gap still exists in the investigation how a combined MPC with MOEA is applicable for real-time control of large-scale water systems, especially for a real-time multi-reservoir operation under multiple objectives.

In this thesis, we discuss multi-objective MPC (MOMPC) frameworks for real-time operation of multi-reservoir systems addressing computational efficiency, multi-objective optimization and multi-criteria decision making. Real-world case studies in Myanmar are presented to demonstrate the capability of the proposed methods.

1.6. RESEARCH QUESTION

Water demand is being increased everywhere due to population growth, urbanization and food security. Thus, it may be required to improve operating rules of existing reservoirs to adopt changing needs of the future. Based on that, the main research question of this thesis is:

"Can MPC be used to meet the operational objectives of a multi-reservoir system?"

This question is answered by the following sub-questions.

(a)Does MPC have the potential to improve the real-time operation of a multi-reservoir system?
(b)Considering the multi-objective operation of a reservoir system, what can be done to improve the flexibility of a classical MPC?

Based on the above questions, we first review the recent developments and discuss the possibility of applying MPC in reservoir operation. Secondly, in order to implement MPC, we develop a model of a reservoir network including river channels and reservoirs. Thirdly, this thesis examines the feasibility of using MPC to operate reservoirs. Finally, this thesis presents a multi-objective Model Predictive Control (MOMPC) scheme for real-time control of a multi-reservoir system that is less subjective than classical MPC formulations when solving a multi-objective control problem.

1.7. DISSERTATION OUTLINE

Chapter 2 presents an overview of available methods for multi-reservoir operation and focuses on developing a new framework based on MPC strategy for real-time multi-reservoir operation under multiple objectives.

In Chapter 3, hydrodynamic modelling of the study area, i.e. the Sittaung river basin in Myanmar, is discussed involving rainfall-runoff modelling with the Sacramento model.

Chapter 4 demonstrates that a proposed MPC framework is capable to mitigate flood risk by improving the current reservoir operating rule in the study area.

Chapter 5 focuses on a multi-objective optimization in multi-reservoir operation and presents how to make a decision using the different multi-criteria decision-making methods.

Chapter 6 discusses the potential of improving reservoir operation in the Sittaung river basin.

Finally, conclusions on the implementation of MOMPC in real world situation are discussed and suggestions for future study are presented. Figure 1.5 shows a scheme of the thesis outline.

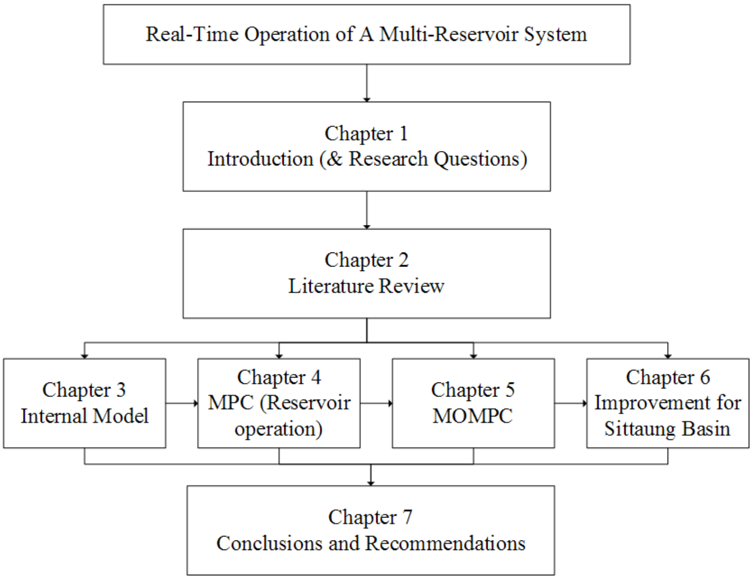

Figure 1.5: Scheme of the thesis outline

2

Optimal Operation of a Network of Multi-Purpose Reservoirs

Due to the effects of climate change and population growth, reservoirs play a more and more important role in water resources management. The management of a multi-reservoir system is complex due to the curse of dimensionalities, nonlinearities and conflicts between different objectives. The optimal operation of a multi-reservoir system operation typically involves optimization and simulation models, which can provide the quantitative information to improve operational water management. The objectives of this chapter are to extend previous state-of-the-art reviews in the operational management of a network of multi-purpose reservoirs with recent developments and to focus on the application of Model Predictive Control for real time control of a reservoir system.

Parts of this chapter have been published in Lin and Rutten [2016].

2

2.1. Introduction

Nowadays, effective water management becomes more vital all over the world due to the effects of climate change and population growth [Arnell, 1999] and, thus, reservoirs play more and more important role in water resources management. Reservoirs can be used for multiple-purposes such as flood protection for downstream areas, irrigation, municipal and industrial water supply, hydropower generation, water quality management, recreation, low flow augmentation and so on. The management of a reservoir system is complex due to conflicting interest between various objectives [Fronza et al., 1977]. For example, demands for irrigation, hydropower generation and recreation are competing each other due to limited storage capacity of a reservoir. Furthermore, flood control operation based on allowable downstream flow rates conflicts to meeting requirements for other purposes. In addition, reservoir operations also need to consider for maximizing a reliability of water supply while minimizing the operational cost. Therefore, in operation of multi-reservoir systems it is important to address various interactions and trade-offs between conflicting objectives when searching the optimal release decisions.

For a water system composed of more than one reservoir, multi-reservoir release decisions are able to improve the operation of hydropower generation and flood prevention by considering the coordination among them [Chen et al., 2013]. Considering a hydrological condition related to spatial distribution of rainfall intensity, some reservoirs are still able to store the water, while other reservoirs are already spilling into the downstream river in which water losses occur from the system. Thus, multi-reservoir operation is a valuable and effective approach to compromise flood control, hydropower generation and comprehensive utilization of water resources of a river basin. The analysis of a multi-purpose reservoir system typically involves optimization and simulation models which can provide the quantitative information to improve operational management. An optimization model is used to minimize or maximize the objective function subject to system constraints and a simulation model is used to evaluate how a water system behaves under a given set of control actions. In the past, optimization problems have been usually solved by using Linear Programming (LP) [Needham et al., 2000], Dynamic Programming (DP) [Chandramouli and Raman, 2001] Quadratic Programming (QP), [Myo Lin et al., 2018] Non-Linear Programming (NLP) [Tejada-Guibert et al., 1990] and multi-objective evolutionary algorithm (MOEA) [Reed et al., 2013]. A reservoir system simulation can be done by using hydrological models or hydraulic models, for example, HEC-5 [Wei and Hsu, 2008], HEC-ResSim developed by US Army Corps of Engineers (`https://www.hec.usace.army.mil/software/hec-ressim/`), MIKE 11 [Ngo et al., 2007] and SOBEK [Tian et al., 2015].

Recently, an advanced control strategy like the Model Predictive Control (MPC) has also been applied in the real-time control of multi-reservoir systems [Ficchì et al., 2016; Delgoda et al., 2013; Breckpot et al., 2013; Schwanenberg et al., 2015]. The main advantage of MPC is the fact that future events are taken into account at every control time-step by using receding horizon principle. Based on this approach MPC optimizes the control problem over a prediction horizon, but only the first optimal control action is implemented, after getting the new measurement the system is updated and the optimization is repeated for next time-step. In this way, MPC controller manipulates the system to achieve the desired objectives and has a high performance compared to the classical control methods like feedback or feedforward control [van Overloop, 2006b]. The objectives of this chapter are to review the developed methodologies in the field of operation of multi-reservoir systems, and to focus on the application of MPC for the control of a large scale reservoir system.

2.2. RESERVOIR SYSTEM ANALYSIS

The formulation of a reservoir system analysis typically involves three main parts which are inflow prediction with a rainfall- runoff model, finding the optimal reservoir releases with an optimization algorithm and river flow simulation with the hydrological or hydrodynamic model. Rainfall runoff modelling is beyond the scope of this chapter and we mainly discuss on optimization and river flow simulation models.

2.2.1. SIMPLIFIED MODEL OF RESERVOIRS AND A RIVER SYSTEM

For real-time operation, a simplified model of a river system is applied to deal with nonlinearity and computational efficiency. This simplified model is still able to capture system dynamics for operational purposes [van Overloop, 2006b; Tian et al., 2015; Xu, 2013]. Generally, the dynamics of a water system can be described as:

$$x(k+1) = f(x(k), u(k), d(k)) \tag{2.1}$$

where x are the states (e.g. storage volumes or water levels of the system), u are the control inputs (e.g. control releases from reservoirs), d are the disturbances (e.g. inflow to reservoirs or river reaches).

In a reservoir system; the changes of storage over time in each reservoir can be modelled by using the following mass balance equation:

$$V_i(k+1) = V_i(k) + \left[Q_{in,i}(k) - Q_{out,i}(k)\right]\Delta t \tag{2.2}$$

where V_i= storage volume of the reservoir i (m^3), $Q_{\text{in},i}$= inflow into reservoir i (m^3/s), $Q_{\text{out},i}$= outflow from reservoir i (m^3/s),Δt = time difference between time step k and $k+1$ (s), k = time step index. The losses from a reservoir (e.g. evaporation, seepage) and the precipitation over a reservoir surface area are being neglected for simplification in Equation (2.2). Consider each reservoir has two outlet structures for operational management, a spillway and a conduit. Among these structures, the spillway is a free overflow structure with no gates, thus, it cannot be controlled. However, the release from a conduit can be controlled by gates to achieve the management objectives. In general, the flow from a weir or a sluice gate can be occurred free flow or submerged flow which depends on the downstream water level condition. In this study, the crest levels of spillway and conduit are designed high enough than downstream channel bed level. Therefore, the structure flows can be described as free flow condition by using following equations [Chow, 1959]. Free over flow from spillway i with fixed crest can be can be determined by:

$$Q_{s,i}(k) = \frac{2}{3}C_{s,i}W_{s,i}\sqrt{\frac{2}{3}g}(h_{up,i}(k) - h_{cr,i})^{\frac{3}{2}} \tag{2.3}$$

2

Free flow from the conduit can also be determined by:

$$Q_{g,i}(k) = C_{g,i} W_{g,i} \mu_{g,i} (h_{g,i}(k) - h_{cr,i}) \sqrt{2g\left[(h_{up,i}(k) - h_{cr,i}) + \mu_{g,i}(h_{g,i}(k) - h_{cr,i})\right]} \quad (2.4)$$

where $Q_{s,i}$= outflow from the spillway i (m^3/s), $Q_{g,i}$= outflow from the conduit (m^3/s), C_g= calibration coefficient, W_g= width of the structure (m), μ_g= contraction coefficient, h_{up}= upstream water level (m), h_{cr}= crest level of structure (m), h_g= conduit gate height (m), g= gravitational acceleration (= 9.81 m^2/s). These structure equations are non-linear. In this study, the linear internal model is used for MPC formulation. Therefore, first order Taylor expansion is applied to Equation (2.3) and (2.4) in order to match with internal model [van Overloop, 2006b]. Equation (2.3) and (2.4) become as follows:

$$Q_{s,i}(k+1) = Q_{s,i}(k) + C_{g,i} W_{g,i} \sqrt{\frac{2}{3} g (h_{up,i}(k) - h_{cr,i})} \Delta h_{up,i}(k) \quad (2.5)$$

$$\begin{aligned} Q_{g,i}(k+1) &= Q_{g,i} + \frac{g C_{g,i} W_{g,i} \mu_{g,i} (h_{g,i}(k) - h_{cr,i})}{\sqrt{2g\left(h_{up,i}(k) - (h_{cr,i} + \mu_{g,i}(h_{g,i}(k) - h_{cr,i}))\right)}} \Delta h_{up,i}(k) \\ &+ C_g W_{g,i} \mu_{g,i} \sqrt{2g\left(h_{up,i}(k) - (h_{cr,i} + \mu_{g,i}(h_{g,i}(k) - h_{cr,i}))\right)} \\ &- \frac{g C_{g,i} W_{g,i} \mu_{g,i} (h_{g,i}(k) - h_{cr,i})}{\sqrt{2g\left(h_{up,i}(k) - (h_{cr,i} + \mu_{g,i}(h_{g,i}(k) - h_{cr,i}))\right)}} \Delta h_{g,i}(k) \end{aligned} \quad (2.6)$$

Then, Equation (2.2) can be rewritten for i^{th} reservoir as:

$$V_i(k+1) = V_i(k) + \left[Q_{\mathrm{in},i}(k) - Q_{\mathrm{s},i}(k) - Q_{\mathrm{g},i}(k)\right] \Delta t \quad (2.7)$$

And water level at reservoir is given by:

$$h_i(k+1) = h_i(k) + \frac{\Delta t}{A_i} \left[Q_{\mathrm{in},i}(k) - Q_{\mathrm{s},i}(k) - Q_{\mathrm{g},i}(k)\right] \quad (2.8)$$

where h_i= water level of reservoir i (m). For river and its tributaries, the water movement along a channel can be expressed mathematically by the principle of conservation of mass and momentum. The governing equations for unsteady one-dimensional open channel flows are well known as De Saint Venant's Equation (2.9) and (2.10) [Chow, 1959].

$$\frac{\partial Q}{\partial x} + \frac{\partial A_f}{\partial t} = q \quad (2.9)$$

$$\frac{\partial Q}{\partial t} + \frac{\partial (Qv)}{\partial x} + g A_f \frac{\partial h_r}{\partial x} + \frac{g Q|Q|}{C_e^2 R_f A_f} = 0 \quad (2.10)$$

where A_f= wetted area of the flow (m^2), q= lateral inflow (m^3/s), v= mean velocity (m/s), h_r= water depth above datum (m), C_e= Chezy's friction coefficient (m$^{1/2}$/s), R_f= hydraulic radius (m). These partial differential equations have no analytical solution yet and the numerical solution can be found by discretizing in time and space. The several numerical techniques are available to solve these partial differential equations. The staggered grids and implicit integration scheme developed by Stelling and Duinmeijer [2003] and discretized scheme by Xu [2013] is adopted to solve Equation (2.9) and (2.10) in this study. The advantage to use this method is that it can deal with rapidly varied flow with a large range of Froude numbers.

2.2.2. CONTROL OBJECTIVES AND CONSTRAINTS

Reservoir operations depend on desired objectives and decision variables, objective functions, and constraints vary for different types of operational problems. The control objectives of multipurpose considerations might include two or more purposes which are as follows:

- Minimize flood risk at downstream area
- Minimize erosion and sedimentation
- Minimize water supply shortages for irrigation, municipal and industrial
- Maximize energy production
- Minimize operational cost
- Maximize the environmental flow supply
- Maximize the length of navigation period

Therefore, multipurpose reservoir operation needs to address various interactions and trade-offs between objectives, which are sometimes competitive or conflicting. For example, releases may be required for hydropower generation, at the same time as releases need to be restricted for the prevention of downstream flooding. The control objectives for irrigation and municipal water supply are to minimize the shortage between demand and supply. The constraints of the water systems can be classified as two types; hard and soft constraints. Hard constraints are physical limitations such as storage capacity of reservoir, maximum release rates of gate, spillway and pump capacity. Examples of soft constraints include legal restrictions, contracted water deliveries and coordination between water authorities. In a mathematical representation, a general form of a multi-objectives control problem is described as:

$$\min J(u) = \{J_1(u), J_2(u), \ldots, J_m(u)\} \tag{2.11a}$$

subject to

$$G_a(u) \leq 0, \quad a = 1, 2, \ldots, n_I \tag{2.11b}$$

$$H_b(u) = 0, \quad b = 1, 2, \ldots, n_E \tag{2.11c}$$

where there are m objectives, n_I inequality constraints, n_E equality constraints and n decision variables. A traditional approach for analyzing trade-offs between various objectives involves treating each objective as a weighted component of an objective function. Thus, the overall objective function is the sum of each component multiplied by a weighting factor reflecting the relative importance of that objective. Thus, Equation (2.11) can be expressed as follows:

$$\min J(u) = \sum_{i=1}^{N\times m} w_i J_i(u) \tag{2.12a}$$

$$\sum_{i=1}^{N\times m} w_i = 1 \tag{2.12b}$$

where N is number of reservoirs in the system and w_i is weight factor for i^{th} objective. However, this method is limited to find all Pareto optimal solution in a single run. The optimal solutions can be found by changing weight factors in many times. Therefore, it is subjective to find a compromise solution without having the detail information represented for the requirements of all parties.

2.2.3. Optimization methods

In reservoir operation, optimization models have been used to determine the optimal release decisions in order to solve the conflicting interest between two or more objectives. An extensive literature review shows that no general algorithm exists in the field of optimization of reservoir operations. The choice of optimization methods depends on the characteristics of reservoir system, data availability, desired objectives and system constraints [Labadie, 2004; Simonovic, 1992; Yeh, 1985]. LP, DP, QP and MOEA are commonly used for reservoir system optimization [Adeyemo and Stretch, 2018; Labadie, 2004; Yeh, 1985].

Linear Programming

Linear programming is often used for optimization problems in which the objective function and constraint are linear. For example, considering a reservoir with the constant release rates for environment flow or firm yield that is maximized subject to constraints included the reservoir storage capacity and conduit outflow.

$$\max \sum_{k=1}^{N} Q_g(k) \tag{2.13a}$$

subject to

$$V(k+1) = V(k) + \left[Q_{in}(k) - (Q_g(k) + Q_o(k))\right]\Delta t, \quad (k = 1, 2, .., N) \tag{2.13b}$$

$$V_{\min} \le V(k) \le V_{\max} \tag{2.13c}$$

$$Q_{g,\min} \le Q_g(k) \le Q_{g,\max} \tag{2.13d}$$

where V = storage capacity of reservoir (m^3), Q_g= constant release rate (m^3/day), Q_o=losses from reservoir (m^3/day) and Δt=time difference between time step k and $k+1$ (day). Needham et al. [2000] presented the application of the mixed-integer linear programming model (HEC-FCLP developed by U.S Army Corps of Engineers) in coordinated operation of the three reservoirs in the Iowa and Des Moines rivers. The authors determined the optimal release decisions by using LP and Muskingum linear channel routing technique is applied to compute reservoir storage and river flow. Penalties for rate of change of storage, release and flow rate are used in the objective function which subject to continuity constraints for reservoir storage and release capacities. This model is based on reservoir storage balancing approach and reservoir's water level balancing approach are presented in Wei and Hsu [2008].

Wei and Hsu [2008] proposed a joint operation procedure for a real-time control of two reservoirs that minimized the flood risk at two control points. The authors applied the back-propagation neural network (BPNN) to forecast the hourly inflow to the system. The Balanced Water Level Index (BWLI) method was developed to determine reservoir releases and the mixed-integer linear programming (MILP) was applied to determine real-time reservoir releases during floods. BWLI method is based on balancing water levels among reservoirs. A main advantage of this method is that releases of reservoirs are based on higher water level index to maintain the same degree of risk. Muskingum linear channel routing was applied to simulate streamflow along a reach between two reservoirs and connected rivers. The main limitation inherent to LP model is that the objective function and every constraint need to be linear. In reality, the dynamics of a water system are non-linear in nature. In addition, linear programming is limited to solve the problems involved probabilistic nature and stochastic dynamic programming (SDP) is commonly used to solve such problems.

DYNAMIC PROGRAMING (DP)

Dynamic programming developed by Richard Bellman is often used to solve the complex optimization problems. In this approach, the given problem is decomposed into a series of sub-problems which are solved recursively, after that their solutions are combined to get an overall solution. The main advantages of this approach are able to deal with non-linearity and stochastic features which characterize in most water systems [Yeh, 1985]. A deterministic dynamic programming has been successful applied in reservoir operation, for example, development of reservoir operating policies for flood control using folded dynamic programming [Nagesh Kumar et al., 2010], multi-reservoir operation using dynamic programming and neural network [Chandramouli and Raman, 2001], improvement of computation efficiency in dynamic programming by using parallel computing [Li et al., 2014]. A useful way to handle uncertain variables in reservoir operation is to use stochastic formulation of dynamic programming called SDP which uses conditional probability distribution function to deal with the stochastic nature of inflow to reservoir. In fact, SDP is a suitable approach for solving optimization problems involved uncertain or stochastic features.

Chen et al. [2013] applied the multi stage dynamic programming technique in joint operation of cascade reservoirs. The authors presented the applicability of the dynamic control of flood limit water level (DC-FLWL) method for the effective trade-offs between the flood control and hydropower generation. To alleviate the computational problems for a complex reservoir system, two cascade reservoirs were considered as an "aggregated reservoir" using decomposition and coordination approach. This approach was able to generate more hydropower from a cascade reservoir system while satisfying safety standards for flood control. However, the DC-FLWL method will become more and more complex in practice when a number of reservoirs in a water system is increased. Braga et al. [1991] used the SDP to maximize the monthly hydropower production of the three reservoirs in Brazil. The online SDP optimization is used to find the optimal set of reservoir releases by using the probability transition matrices and the value of the stored water in all of the reservoirs for the particular month determined by the off-line deterministic DP. This study shows that a combination of off-line and on-line procedures which can reduce the computational requirements inherent in a multi-dimensional stochastic DP. Kelman et al. [1990], Stedinger et al. [1984] and Anvari et al. [2014] also presented the applications of SDP in reservoir operation optimization.

The above studies show that how to solve control problems in small scale reservoir systems (involved two or three reservoirs) using DP or SDP. In case of large-scale reservoir systems, the control problems become more complex because increasing reservoirs and control objectives, nonlinearity in the system dynamics and the presence of stochastic variables. Cervellera et al. [2006] presented a method to alleviate curse of dimensionality problem in the operation of a reservoir system by developing an efficient state space discretization schemes with orthogonal arrays. Their results showed that an improvement in SDP application for a large-scale water system, however, further investigation is required for solving more complex problems. In fact, the main limitation of SDP is its computational complexity, the so called curse of dimensionality caused by exponential growth on states and control dimensions when a number of states is increased [Castelletti et al., 2008].

QUADRATIC PROGRAMING (QP)

In a control problem, when an objective function J is quadratic and the constraints are linear in decision variables u, then such problem can be solved by using quadratic programming. Its general form is expressed as:

$$\min J(u) = \frac{1}{2} u^T R_u u + q_u^T u \tag{2.14a}$$

subject to

$$Gu \le b_e \tag{2.14b}$$

$$Hu = d_e \tag{2.14c}$$

where R_u is a symmetric matrix contained all of the quadratic terms, q_u is a coefficient matrix contained all of the linear terms. b_e and d_e are referred as to inequality and equality constraints respectively. The advantage of this method is that easy computation of the derivative of the objective function given as a quadratic scheme and the minimum of the objective function can be found by making the derivative equal to zero. Wasimi and Kitanidis [1983] presented the real-time operation of a reservoir system for flood control. In this study, a reservoir system was represented in state-space form with quadratic cost functions subject to linear equality constraints given. This optimization problem was solved in the framework of discrete-time Linear Quadratic Gaussian (LQG) control and used the reduced-order state-space unit hydrographs to forecast storm runoff from the effective rainfall. The channel routing was performed by using the linear Muskingum channel routing technique. This approach is applicable for real time flood control problem; however, it is valid only under moderate flood conditions. In MPC formulation, quadratic programming has been also applied to optimize a quadratic cost function for flood control [Tian et al., 2015], water level control of irrigation canal [van Overloop, 2006b; Sadowska et al., 2014] and control of a drainage system [Maestre et al., 2013].

MULTI-OBJECTIVE EVOLUTIONARY ALGORITHM (MOEA)

A number of optimal solutions exists in solving MOOPs, generally defined as the Pareto optimal solutions. The traditional approaches to find the Pareto optima consider combination of all objectives into a single objective function solved by using a weighted-sum or a constraint method in which the Pareto optimal set can be obtained by changing the parameter settings in several times of optimization. To overcome this difficulty , EAs have been gained attention to solve MOOPs in water resources management because its ability to search the Pareto optimal solutions simultaneously in a single optimization run [Nicklow et al., 2010; Reed et al., 2013]. In addition, EA is able to handle non-linear, non-convex and discontinuous optimization problems.

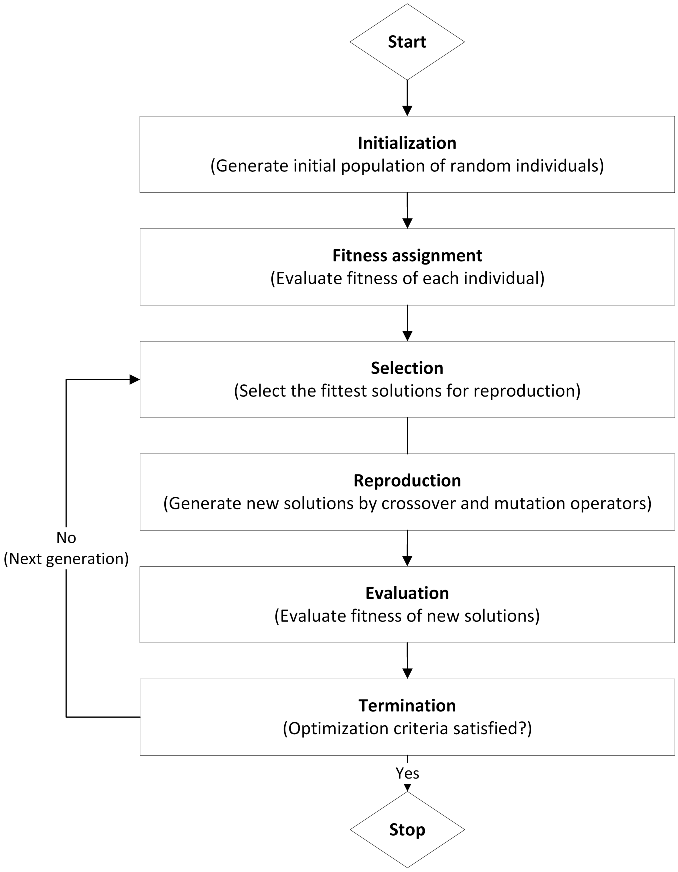

Figure 2.1: General framework of evolutionary algorithm

Since 1970s, the growing interest on solving complex optimization problems has served to develop several EA methodologies, such as genetic algorithms, evolutionary programming, evolutionary strategies and genetic programming. All these methods are based on the natural evolution process involved two basic schemes, namely selection and variation. First, a set of solution candidates, formally called initial population, is created. In the selection process, the objective functions or fitness functions are used to evaluate the fitness of each individual solution. The high fitness solutions are selected for reproduction, while low fitness solutions are removed from the population. Then variation process generates new population using crossover and mutation operators. The crossover operator generates offspring solutions by recombination of a certain number of parent solutions according to a given crossover rate. The mutation operator modifies the genes of individual solutions to maintain genetic diversity according to a given mutation rate. In the context of EA, a term "generation" is referred to a loop of fitness evaluation, selection, recombination and mutation. This loop is repeated to search a set of Pareto optimal solution until a given termination criterion is met. A generalized framework of EA is shown in Figure 2.1.

2.2.4. Simulation Models

The simulation model provides the response of the system for certain inputs. This model typically computes the storage volumes, water levels and discharge of a water system. Various simulation models have been applied in literature. The U.S. Army Corps of Engineers developed the reservoir system simulation software like HEC-3, HEC-5 and HEC-ResSim for various purposes, e.g., conservation, flood control and hydropower generation and environmental flow. HEC-ResSim is freely available online at http://www.hec.usace.army.mil/software/hec-ressim. Recent studies also applied the mass-balance accounting approach and the Muskingum channel routing method in reservoir system analysis [Braga et al., 1991; Needham et al., 2000; Wasimi and Kitanidis, 1983; Wei and Hsu, 2008]. For a detailed simulation of flood control operations, Mike 11, HEC-RAS, SOBEK and other hydrodynamic models are used to study the dynamics of a flood wave moving along a stream (or) channel. These models are able to represent the dynamics of open channel flow by applying De st. Venant equations. Ngo et al. [2007] proposed a method to optimize a multi-purpose reservoir rule curve using a combination of MIKE 11 simulation model and the shuffled complex evolution algorithm. This study focuses on the trade-offs between flood control operation and hydropower generation of the Hoa Binh reservoir in Vietnam. Recently, Seibert et al. [2014] presented the potential of coordinated reservoir operation for flood mitigation in a large-scale water system composed of nine reservoirs. They used two-dimensional (2D) hydrodynamic model to improve the model performance instead of using hydrological channel routing method. The result shows that 2D hydrodynamic model is able to improve model performance compared to simplified hydrological routing technique, however, the boundary conditions should have sufficient quality. In this study, the authors mainly focus on the evaluation of model performance and only consider a single objective (i.e. flood control) for operation of a reservoir system.

In the past literature, several methods are available for optimal operations of multi-reservoir systems in which optimization and simulation models need to be effectively used in combination for improving model performance. MPC has such ability because optimization and simulation or internal model are main components in MPC formulation. Moreover, MPC can deal with multi-variable processes, system constraints and uncertainty. Based on these capabilities, MPC is a promising method for real-time control of a multi-reservoir system.

2.3. MODEL PREDICTIVE CONTROL

MPC controller consists of the three main components, prediction of system behavior using a process or an internal model, optimization of desired objectives subject to given constraints and application of the receding horizon principle. A structure diagram of MPC is shown in Figure 1.4. As a model-based control method, MPC uses an internal model to predictive the future system states along a prediction horizon at every control step. Based on the behaviour of a system, linear or non-linear model is applied as an internal model in MPC formulation. In reality, the nature of a water system is non-linear. As described in Section 2, De Saint Venant's equations, i.e. Equation (9) and (10), are commonly used to represent the dynamics of a water system in MPC formulation [van Overloop, 2006b; Tian et al., 2015; Xu, 2013]. These equations can be written as a state space form which is usually used to solve a multivariable control problem. A general state space description of a controlled water system is expressed as:

$$x(k+1) = A_x(k)x(k) + B_u(k)u(k) + D_d(k)d(k) \tag{2.15a}$$

$$y(k) = Cx(k) \tag{2.15b}$$

where $x(k)$ is the system state, $u(k)$ is the control input and $d(k)$ is the disturbance to the system. $A_x(k)$, $B_u(k)$ and $D_d(k)$ are system matrix, control input matrix and disturbance matrix respectively. For deterministic MPC formulation, the current state and the disturbance are known. The control inputs can be determined by optimizing an objective function. The discretization of Equation (2.15a) in space and time provides a numerical solution of the system dynamics over a prediction horizon.

For open water systems, the objective function is usually formulated to minimize the deviations of water levels from its reference signals and changes of control setting. A generalized form given by van Overloop [2006b] is:

$$
\begin{aligned}
J(u) = &\sum_{j=1}^{N_P}\sum_{i=1}^{M}(h_i(k+j)-h_{ref,i}(k+j))^T Q_{h,i}(h_i(k+j)-h_{ref,i}(k+j))\\
&+\sum_{j=1}^{N_P}\sum_{i=1}^{L}(\Delta u_i(k+j))^T R_{u,i}(\Delta u_i(k+j))
\end{aligned} \tag{2.16a}
$$

$$\Delta u(k+1) = u(k+1)-u(k) \tag{2.16b}$$

subject to

$$h_i(k+1) = A_h(k)h_i(k)+B_u(k)u_i(k)+D_d(k)d_i(k) \tag{2.16c}$$

$$h_{\min,i} \le h_i(k) \le h_{\max,i} \tag{2.16d}$$

$$u_{\min,i} \le u_i(k) \le u_{\max,i} \tag{2.16e}$$

where N_P= number of step over the prediction horizon, M= number of channel reaches, L= number of structures, h_i= water level of reach i, $h_{ref,i}$= reference water level of reach i, $Q_{h,i}$= penalty on error in water level i, Δu_i= change in control flow at structure i, $R_{u,i}$= penalty on change in control flow at structure i. For a multi-objective control problem, each management objective is formulated as a sub-objective function in the classical MPC formulation. Each of these sub-objective functions is multiplied with a given weight factor which represents a relative importance of each objective. All sub-objective functions are summed up to form a single objective function as follows:

$$\min J(u) = \sum_{j=1}^{N_P}\left(w_1 J_1(u(k+j)) + w_2 J_2(u(k+j)) + \ldots + w_m J_m(u(k+j))\right) \tag{2.17}$$

The management goal can be achieved by minimizing this objective function. MPC formulation is based on the current measurements and future system states for finding required control inputs at every control time step. Moreover, MPC can handle the conflicting objectives and constraints. In this way, MPC can provide a better performance to control a water system compared to the other control methods. van Overloop [2006b] presented the potential of MPC in controlling irrigation and drainage systems. A comparison was done between MPC and the conventional control methods, feedback control and feedforward control. The result shows that MPC outperforms feedback control and feedforward control in periods of extreme load. Moreover, a field experiment of MPC for an actual irrigation system shows that irrigation water can be delivered to the users efficiently and no constraints are violated [van Overloop et al., 2010]. In recent years, MPC has successfully applied in water resources management for various purposes such as irrigation water supply, drainage control, flood prevention and hydropower generation.

2.3.1. Development of MPC in real-time reservoir operation

Typically, a reservoir system is composed of reservoirs, river reaches and other hydraulic structures. The integrator delay model [Schuurmans et al., 1999] or the Saint Venant model [van Overloop, 2006b] are usually used as an internal model to calculate the water levels and flows of a reservoir system. However, the integrator delay model only works for defined delay time and storage area of a specific water level of a river reach [Breckpot et al., 2013; van Overloop, 2006b] which makes it difficult to use for a flood control problem. A better way to describe the dynamics of a water system is using the Saint-Venant equations which can be discretized in space and time to obtain the changes of water levels and flows along an open channel [Xu et al., 2012]. The structure equations are also used in an internal model to determine outflows from a reservoir. These structure equations need to be linearized when a linear time-varying state space model is used in MPC formulation. Generally, the gate discharge is used as a control variable to avoid nonlinearity in the structure equation [Breckpot et al., 2013]. However, the gate height can also be used as a control variable in MPC formulation [Tian et al., 2015]. The discretization of the Saint Venant model with a small grid size and a small-time step require long computational time which is not preferred for real-time control of a large-scale water system. A large time step control scheme proposed by Tian et al. [2015] shows an improvement to reduce the computational time in MPC formulation and is able to control a large-scale water system. Chapter 4 presents the extension of this technique to operate a multi-reservoir system under multiple objectives.

A standard MPC formulation is based on a deterministic approach which means that the disturbances are known over a prediction horizon. In reality, inflow or disturbance to a controlled water system is uncertain in nature. To deal with uncertainty, the standard MPC has been extended as multiple MPC based on probabilities of occurrence of the best, worst and most probable cases [van Overloop et al., 2008], adaptive Multi-MPC based on multiple model configuration [Delgoda et al., 2013] and tree-based MPC (TB-MPC) based on ensemble stream flow prediction [Raso et al., 2014]. These studies provide a solution to deal with uncertainty in inflow prediction and improve the operational performance of MPC. Ficchì et al. [2016] applied the TB-MPC method to control a four-reservoir system in the Seine River basin and compared the performance of MPC with perfect forecasts, deterministic forecasts and ensemble forecasts. The results indicate that the use of ensemble forecast provides an acceptable performance compared to the results of perfect forecast. However, the computation time of TB-MPC is 7-times greater than the standard MPC [Ficchì et al., 2016]. The efficient multi-scenario MPC proposed by Tian et al. [2017] applied the adaptive control resolution approach to reduce the computational time in the formulation of MPC with ensemble streamflow forecasts.

In recent literature, most of the MPC formulations for real-time control of a reservoir system focus on flood control at the downstream river reaches [Breckpot et al., 2013; Delgoda et al., 2013; Ficchì et al., 2016; Schwanenberg et al., 2015]. A multi-objective operation needs to be considered when a reservoir is used for multiple purposes. A weighted-sum method or a constraint method are often applied to solve a multi-objective control problem in the MPC formulation [Myo Lin et al., 2018; Uysal et al., 2018]. However, these methods are limited to find all Pareto optimal solutions in a single run [Deb, 2014]. More flexible approach to search a Pareto optimal set is using evolutionary multi-objective optimization method which has an ability to deal with multiple objectives, nonlinearity, discreteness and nonconvex objective functions [Reed et al., 2013]. This technique has been successfully incorporated with MPC to solve water management problems [Chiang and Willems, 2015; Tian et al., 2019; Vermuyten et al., 2018] and is also promising to use for real-time operation of a multi-reservoir system with multiple control objectives. As receding horizon principle is applied in MPC, it is necessary to select an optimal solution for implementation at the current time step to move the next step. A multi-criteria decision-making technique can be adopted to fulfill this requirement. A method involved multi-objective evolutionary algorithm, multi-criteria decision-making process and receding horizon principle, is presented in Chapter 5 to control a multi-reservoir system with multiple control objectives.

2.4. CONCLUSIONS

As mention above, optimization and simulation models are the useful tools for operation of a reservoir system. Concerning optimization models, linear programming method is based on trial and error solutions and it is difficult to search optimal solutions for a complex problem involved multi-objective and nonlinearity. Dynamic programming techniques are more complex but can overcome certain limitations of LP. However, it can suffer from the dimensionality problem because the exponential increase in computational time and memory requirements when the system states are increased [Cervellera et al., 2006]. If the control problems are formulated as quadratic cost function with linear constraints then it can be solved by using quadratic programming. Evolutionary algorithm is a powerful tool to find a Pareto optimal set for multi-objective optimization.

Regarding simulation models, HEC-3, HEC-5 and HEC-ResSim are freely available to use for reservoir system simulation. These models have capabilities for hydrological simulation of reservoir operations involving water supply, hydro-power generation and flood control. However, for detailed simulation of flood control operations, Mike 11, HEC-RAS, SOEBEK and other hydrodynamic models are more suitable to capture the dynamic changes of water levels at the downstream control points. A simplified model based on Saint-Venant equations is also applicable to simulate an open water system.

In past literature, several methods are used to control a multi-reservoir system in which optimization and simulation models need to be effectively combined for better system performance. An advanced control method, MPC, has such ability that optimization and simulation models are main components in MPC formulation. Moreover, MPC takes into account the future and current system states to determine the optimal control action at every control time step that provide a better performance for controlling a water system. Even MPC has been widely applied to control various water system, currently, a limited number of studies are available in the literature for multi-reservoir operation under multiple objectives. Therefore, it can be concluded that a gap still exists for control of a large-scale reservoir system (more than 10 reservoirs) and the application of such system approach in practice. To control such large-scale water systems, it is important to select suitable model which should be able to deal with system complexity.

3

Modelling of the Sittaung River System

Hydrodynamic modelling is a prerequisite tool in planning and management of a river system. A hydrodynamic model is a computation model to simulate the movement of water based on the numerical solution of conservation of mass and momentum equations. This model can provide the information about discharge, velocity, water depth, sediment concentration and salinity of a water system. This information is useful to develop better solutions for water management issues such as flooding, sedimentation and water quality.

Parts of this chapter have been published in Myo Lin et al. [2018].

3.1. THE SITTAUNG RIVER BASIN

The Sittaung river is one of four major rivers in Myanmar. Its length is 420 km and the catchment area of this river basin is 34,000 km^2. The Sittaung River flows from north to south through the south central plain of Myanmar and enters to the Andaman Sea. It has 5 main tributaries coming from the east and 8 main tributaries coming from the west. The total population in the river basin is about 5.8 million, which is about 9 percent of Myanmar's total population. The location of the Sittaung River Basin is shown in the map in Figure 3.1. This river basin has been developing fast and facing problems with flooding, sedimentation, river bank erosion and sea water intrusion. Reservoirs have been constructed along tributaries of the Sittaung River for irrigation, hydro power generation and flood control. The sustainable management of this river system is complicated due to the effect of different climate conditions across the basin, competing water use objectives and environmental issues. Therefore, a reliable tool is required to assist the decision-maker for comprehensive planning and management of the Sittaung River system. The physically based model of a river system which is integrated with rainfall-runoff model can be used as a tool to analyse the effects of either a short or a long-term management scenario.

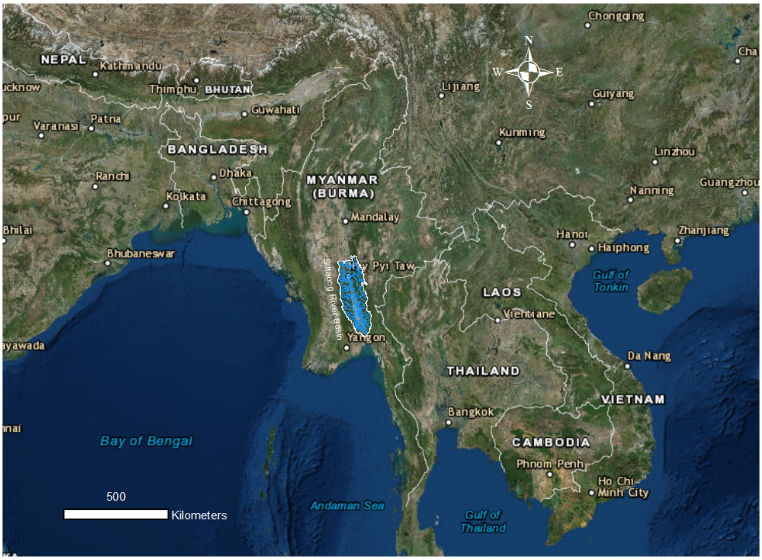

Figure 3.1: Location map of the Sittaung river basin.

3.2. DATA COLLECTION OF THE SITTAUNG RIVER BASIN

This system model consists of three main parts; the outflow estimation of a catchment with a rainfall- runoff model, reservoir model and river flow simulation with a 1D hydrodynamic model. The developed system model is to be used for real time control of a reservoir system in the Sittaung River Basin. The following data are required for modelling work.

1. Rainfall-runoff model - Catchment area, rainfall, soil type, infiltration, land use, ground water level and discharge

2. Reservoir model. - Area vs Capacity, spillway (type, width, design discharge, and gate size), outlet gate, irrigation demand, hydropower demand, rule curve, water level and evaporation.

3. River flow simulation model - Cross sections, initial conditions (water level and discharge for initial state),boundary conditions (tidal data), water level and discharge.

3.2.1. DATA AVAILABILITY

In Myanmar, the Department of Meteorology and Hydrology (DMH) is a main source of meteorological and hydrological data. More than 20 rainfall stations from DMH are monitoring the rainfall in this basin. All these stations are located within the city area and it is impossible to get rainfall data for rural area (catchment area of reservoir). The water level gauge stations from DMH are also monitoring the daily water level and daily discharge at Taungoo and Madauk cities. The long term record of data such as daily rainfall, daily water level and daily discharge are available from most of DMH stations. Moreover, There are more than 20 reservoirs in the basin and every reservoir has a weather station for monitoring the daily rainfall and daily water level of reservoir. In the current situation, a reservoir operator records daily data of reservoir such as water level, rainfall and height of gate opening. These data are daily sent to local office by phone or wireless device. On the same day, these data are reported from offices to offices, from local offices to, regional offices to, Director's Offices and finally to the head office of the Irrigation and Water Utilization Management Department (IWUMD), Naypyitaw.

Along the Sittaung River, there are a total of 11 water level gauge stations from IWUMD, eight stations on the main river and three stations on the tributaries of the Sittaung River. Ordinary gauge readings are usually taken three times a day and tidal gauge readings are taken five times a day. The list of IWUMD water level gauge stations is shown in Appendix A.1 and the location map of gauge stations is shown in Appendix A.2. The operators from the gauge stations daily collect the data in the record book and monthly send it to Hydrology Branch of IWUMD using the postal mail. These delayed processes make effects on real time control of this river system and, therefore, it urgently needs that this monitoring system be upgraded for real time users. At present, hourly time series data of rainfall and water level in this river basin are very limited. DMH plans to install automatic weather stations at the major rivers in Myanmar, consequently, it will be possible to get real time data in near future. Most of the data are currently recorded by using a paper based system.

The survey team gathered the water level data from 8th February to 25th April 2015. The field work also involved the collection of required data of the reservoirs and cross-section survey of the Sittaung river. The data collected for reservoirs contained information about physical features of reservoirs, irrigation supply, hydropower generation, inflow and outflow and water level of reservoir for past five years. The survey team visited a total of nine local and regional offices of IWUMD to collect the data and other information such as monitoring and operation of reservoir. Moreover, we also visited the Phyu and Yenwe dam in the Bago Region and the Paung Laung and Yezin dam in the Naypyitaw Region to examine the management system of reservoirs. Every reservoir has its own rules and regulations for operation and maintenance, which includes duties of staff related to irrigation supply, inspection of the reservoirs and response for emergency situations. Local offices of Irrigation Department operate the reservoirs under instruction of regional office and their experiences. A cross section survey was carried out at (28) places along the Sittaung River, starting from near Pyinmana to its river mouth. The places for cross-sections were selected based on the location of water level gauge stations, on the conditions of access roads and on the flood plan. The surveying work was done by the Survey Branch of IWUMD, Myanmar in cooperation with Delft University of Technology for the research of reducing flood risk in this river basin. The location map of river cross-sections is shown in Appendix A.3. The permanent concrete bench-marks were installed at all river survey points for further investigation. Some photos of bench-marks are shown in Appendix A.4. The banks of the river in the floodplains are composed of clay and sandy silts. They are rather steep and have a height of 3-10 m. Subjected to floods;the adjacent area is protected by embankments at some places in the middle and lower reaches of the river. The cross-sections of the Sittaung river are available in http://resolver.tudelft.nl/uuid:0e642228-c300-4db9-8946-0e9adcb63431.

3.3. RAINFALL RUNOFF MODELLING

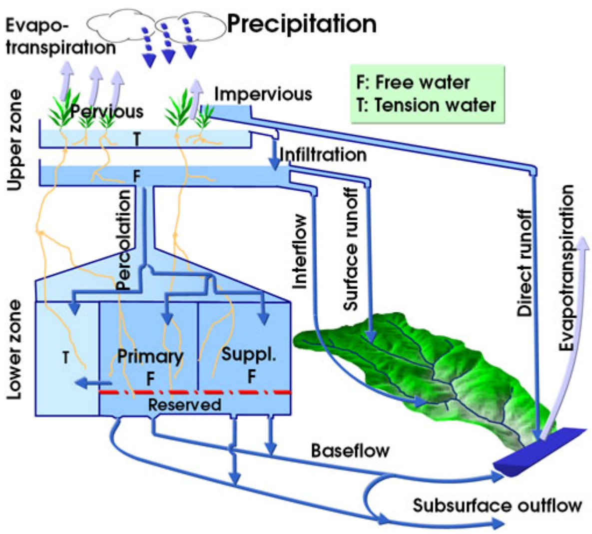

Figure 3.2: Schematic diagram of SACSMA model (http://ldas.gsfc.nasa.gov/nldas/images/SAC_schematic.jpg).

In this study, the SACramento Soil Moisture Accounting (SAC-SMA) model is used to estimate the rainfall runoff relation of a catchment. It is a conceptual hydrological model which was developed in the 1970s to estimate the runoff for small and medium scale catchment areas. The United States's National Weather Service (NWS) uses the SAC-SMA for river runoff forecasting [Koren et al., 1999]. The SAC-SMA model has two soil zones: the upper zone and the lower zone. Each zone has two water components: a free water and a tension water. Soil moisture depletion and soil moisture replenishment in the storage are determined based on precipitation, evapotranspiration, percolation and horizontal outflow. The conceptual diagram of the SAC-MAC is shown in Figure 3.2.

The river basin was divided into 31 sub-catchments assigned to the drainage network. The model inputs are precipitation, potential evapotranspiration, soil parameters and a unit hydrograph. The parameters of SAC-SMA were determined by calibration processes with the observed data [Vrugt et al., 2006].In this study, the Clark's (1945) method [Kull and Feldman, 1998] was used to derive a unit hydrograph.

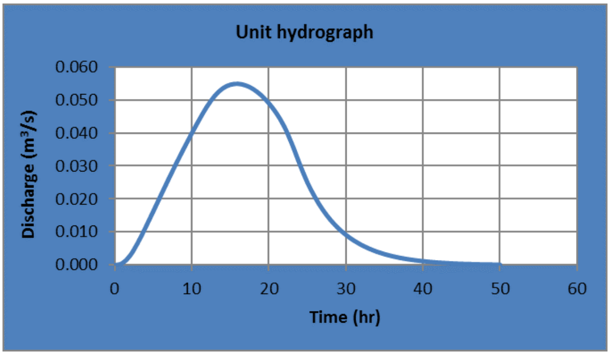

Figure 3.3: Derived unit hydrograph.

The Clark method is based on the time area relations and linear reservoir routing technique to estimate runoff from one unit of effective rainfall [see details in Deltares, 2016]. The two parameters time of concentration Tc and routing parameter k, need to be defined for unit hydrograph derivation. These two parameters can be obtained from the model calibration with the observed rainfall and discharge data. Several empirical formulas are also available to estimate Tc [Sharifi and Hosseini, 2011; Grimaldi et al., 2012]. Kirpich (1940), Kerby (1959) and the NRCS (1986) velocity method were used to determine the Tc values and, an average Tc value of these three methods was used in this study. A developed unit hydrograph is shown in Figure 3.3.

The application of the SAC-SMA model in SOBEK is based on a distributed approach. A catchment is divided into a number of sub-catchments, and the estimated runoff of a sub-catchment is linked with the main river system. The schematization of the SAC-SMA model in SOBEK is shown in Figure 3.4. In this figure, the green nodes represent the sub-catchments in which different rainfall input and parameter sets can be assigned. The areas of sub-catchments are ranging from 100 km^2 to 300 km^2. The SAC-SMA model parameters were manually calibrated with the observed data. Table 3.1 shows calibrated model parameters and its allowable ranges.

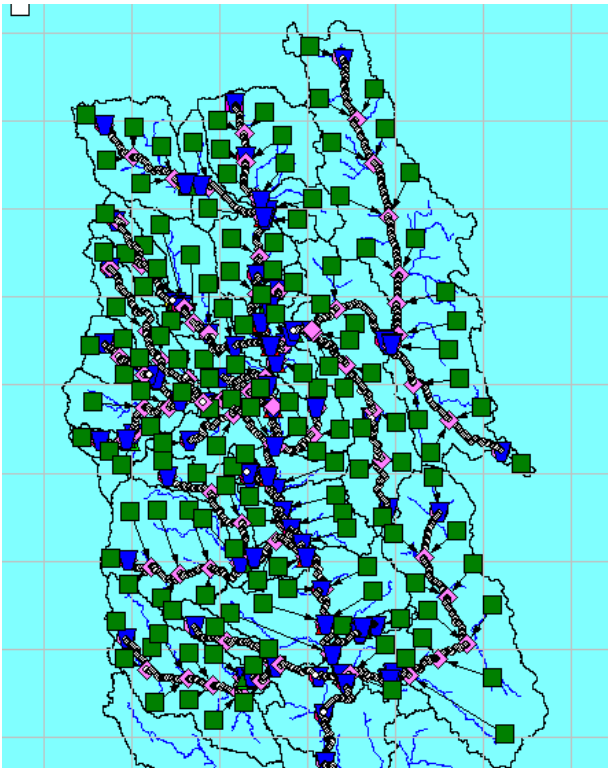

Figure 3.4: Schematization of the Sittaung river system in SOBEK (The blue trapezoidal nodes are cross-sections; the pink diamond nodes are rainfall runoff connections and the white circle nodes are calculation points.).

Table 3.1: Sacramento model parameters used for simulation

No.	Parameter	Description	Used for model	Acceptable range
1	UZTWM	The upper layer tension water capacity (mm)	70	10-300
2	UZFWM	The upper layer free water capacity (mm)	150	5-150
3	UZK	Interflow depletion rate from the upper layer free water storage (day^{-1})	0.1	0.1-0.075
4	ZPERC	Ratio of maximum and minimum percolation rates	10	5-350
5	REXP	Shape parameter of percolation curve	2	1.0-5.0
6	LZTWM	The lower layer tension water capacity (mm)	500	10-500
7	LZFSM	The lower layer supplemental free water capacity (mm)	300	5-400
8	LZFPM	The lower layer primary free water capacity (mm)	550	10-1000
9	LZSK	Depletion rate of the lower layer supplemental free water storage (day^{-1})	0.01	0.01-0.35
10	LZPK	Depletion rate of the lower layer primary free water storage (day^{-1})	0.001	0.001-0.05
11	PFREE	Percolation fraction that goes directly to the lower layer free water storage	0.2	0 0.8
12	PCTIM	Permanent impervious area fraction	0.024	Not given
13	ADIMP	Maximum fraction of an additional area due to saturation	0.2	Not given
14	RSERV	Fraction of lower layer free water not transferable to lower layer tension water	0.3	Not given

3

3.4. 1D HYDRODYNAMIC MODEL

The study area covers the entire Sittaung River system, including all incoming main tributaries from the east and west. The streams were divided into a number of reaches at the junctions of tributaries and at the inflow points of intermediate catchments. The measured cross-sections of the Sittaung River were used as model input. The cross-sections of tributaries were generated by using DEM, bed slope, maximum design discharge of the reservoir and the channel top width obtained from Google Earth images. According to the channel bed slope, the main river can be divided into three parts. The average bed slope of the upper part, from its origin to the junction with Paunglaung stream, is 0.00089 and the middle part, from junction of the Paunglaung to the Taungoo, is 0.0003. The lower part is relatively flat and the bed slope is 0.00017. The SOBEK software package is used for hydrodynamic modelling coupled with the Sacramento rainfall runoff model. The calculation grid sizes of the river reach in SOBEK is 500 m and the calculation time step is 30 minutes.

The existing reservoirs in the Sittaung river basin are considered in the model as well. Each reservoir in the system is represented as a node of given capacity. A reservoir has two outlet structures for the operational management, a spillway and a conduit. Among these structures, the spillway is a free overflow structure with no gates, and thus it cannot be controlled. Therefore, the spillway will be activated when the water level of the reservoir reaches above its crest level. Types and characteristics of the spillways are shown in Table 3. The conduit is a vertical sluice gate and it can be controlled to store or release water from a reservoir. The outflows from both structures are added up at a node at the downstream of the reservoir. The nodes are linked to each other by the reaches. In 2013, an extreme flooding occurred at the upper part of the Sittaung river basin and more than 2000 hectares of agricultural land were inundated. Therefore, this flood event is chosen as a case study and model results are discussed in the following section.

Table 3.2: Types and characteristics of spillways.

No.	Reservoir	Spillway width (m)	Spillway type
1	Sinthe	33.53	Ogee crest with chute
2	Yezin	13.72	Chute
3	Upper Paunglaung	50.29	Ogee
4	Lower Paunglaung	140.5	Ogee crest with stepped chute
5	Naglaik	96.31	Duckbill
6	Chaungmange	24.38	Ogee crest with chute
7	Madam	15.24	Chute
8	Myohla	9.14	Chute
9	Swa	122	Duckbill
10	Pathi	45.72	Chute
11	Kabaung	32.31	Ogee crest with chute

3.5. RESULTS AND DISCUSSION

The model was simulated coupled with the rainfall runoff model (SAC-SMA) using 30 minutes time steps. The SAC-SMA parameters and roughness coefficients of the streams were calibrated by using observed water levels and discharge data of the Taungoo station. The results for the upper part of Sittaung River basin are discussed in this section.

Table 3.3: Performance indices for daily mean discharge and cumulative inflow to reservoirs during calibration for October 2013.

Name of reservoir	Daily mean discharge		Daily mean discharge
	NSE	RMSE (m^3/s)	RMSE(Mm^3)
Sinthe	0.35	16.44	0.08
Yezin	0.07	11.07	0.08
Lower Paunglaung	0.32	101.87	5.93
Naglaik	0.22	13.11	0.21
Chaungmange	0.18	7.89	0.24
Madam	-0.36	1.43	0.28
Myohla	-0.38	1.43	0.08
Swa	0.47	31.68	0.72
Pathi	-0.84	13.21	1.39
Kabaung	0.38	38.45	0.89

Table 3.3 shows the performance indices of model during calibration for October 2013. It is observed that the Nash-Sutcliffe Efficiency (NSE) values for seven reservoirs vary from 0.07 to 0.38. The NSE values are very small when the observed data contains large outliers in it. The NSE values for three reservoirs are less than zero. One of the possible reasons for this outcome might be the use of the same parameters for all catchments.

Furthermore, there are uncertainties associated with the rainfall data. TRMM rainfall analyses were carried out with available observed data. Figure 3.5 presents the model results for two sub-catchments and the comparison between observed data and TRMM rainfall. The rainfall 6 of 7 analysis indicates that the correlation between TRMM and observed data is very low and that temporal variation is large in the hourly scale. Root Mean Squared Error (RMSE) values indicate that the prediction errors are high for daily mean discharge, however, the cumulative inflow are as close to observed data.

Figure 3.5 reports the comparison between the model result and the observed data at the Taungoo gauge station. The NSE value of daily mean discharge at the Taungoo is 0.76 even though the NSE values of the sub-catchments are less than 0.5. The comparison result also shows that there is a close agreement in cumulative flow at the outlet point. The model was validated with longer time series input data using the calibrated roughness coefficients and the SAC-SMA parameters. Figure 3.6 presents the model validation results in terms with water level and discharge at the Taungoo gauge station. It is observed that there are differences between simulated and observed water levels, which may be caused by the use of defined cross-sections or by the effect of infrastructure. The defined cross-sections are used in several tributaries where measurement data are not available.

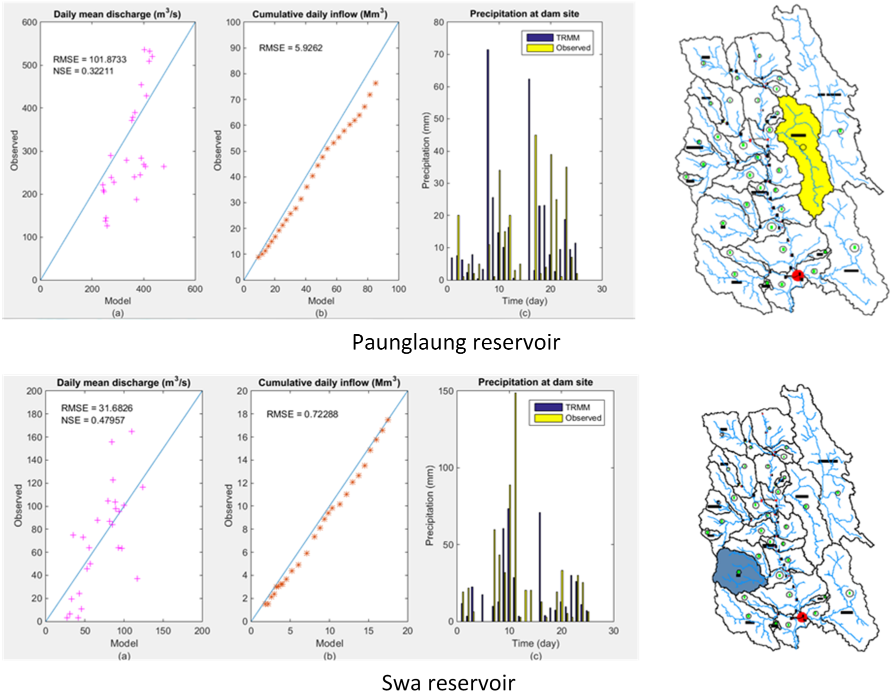

Figure 3.5: (a) Daily inflow to reservoir (b) Cumulative daily inflow (c) TRMM and observed rainfall (Lower Paunglaung reservoir and Swa reservoir.

As for existing infrastructures, there is a bridge near the Taungoo gauge station, of which the hydraulic effects are also not taken into account in the modelling process. The comparison of daily discharge shows that there is a close agreement between simulated and observed discharge, however, for peak discharge, the simulated value is higher than the observed value. A possible reason might be an measurement error or a model error. During 2013 flood event, the water level reached 1 m above its danger level at the Taungoo gauge station. It is not yet clear how to measure the discharge during a flood event. On the other hand, a 2D modelling approach is better than a 1D modelling approach when water overflow the river banks.

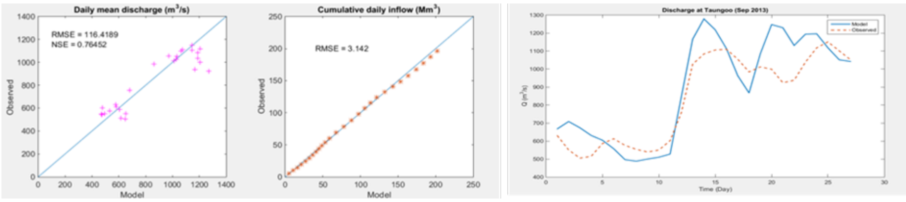

Figure 3.6: Comparison of observed and simulated discharge at the Taungoo gauge station.

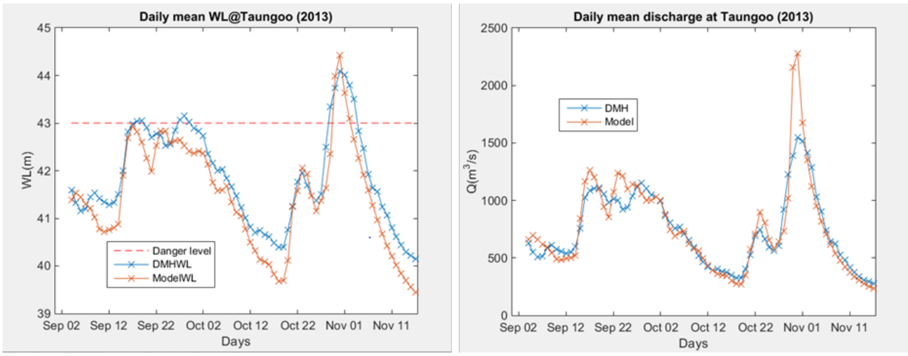

Figure 3.7: Comparison of observed and simulated discharge at the Taungoo gauge station for 2013 flood event.

3.6. CONCLUSIONS

A hydrodynamic model of the Sittaung River is developed by using the SOBEK software package. This model is validated using the observed data of 2013 flood event in the Sittaung River basin. In comparison, for the SAC-SMA modelling, a distributed approach is more suitable to capture the spatial rainfall variability in a catchment. However, an error still exists in TRMM rainfall with temporal variation. Therefore, it is required to correct the TRMM errors using ground rainfall data. Existing monitoring stations are far from being sufficient to provide hydrological and meteorological data like precipitation, run-off, evaporation and water level, and this makes difficult for model calibration and validation. Since existing measuring networks do not have sufficient density, it is necessary to build additional hydrological and meteorological gauging stations in the Sittaung River Basin.

For 1D hydrodynamic modelling, the measured cross-sections are only available for a few locations. The cross-section survey is a time-consuming process and, moreover, also an expensive task. Therefore, it is also interesting to investigate the model performance by using extracted cross-sections from a high-resolution DEM. In general, the model results are similar to the observed data. However, it is observed that there are the differences in observed and simulated water levels as well as in peak discharge. Therefore, the model performance should be investigated with other historical flood events for further improvement.

4

Flood Mitigation through Optimal Operation of a Multi-Reservoir System using Model Predictive Control

Managing a multi-reservoir system is complicated due to conflicting interests among various objectives. This study proposes an optimization-based approach for operations of a multi-reservoir system. An advanced real-time control technique, Model Predictive Control (MPC) is adopted to control a multi-reservoir system with two control objectives, i.e. flood mitigation and water conservation. The case study area is the Sittaung River basin in Myanmar, where the current reservoir operating rule needs to be improved for a more effective operation. A comparison between MPC-based operation and the current operation is presented by using performance indicators. Result shows a reduction of the system's vulnerability by 0.9 percent using MPC. Due to the physical constraint of the reservoirs, it is impossible to completely eliminate the flood risk at Taungoo City during high inflow events. However, the results indicate that the potential flood risk can be mitigated by improving the current operating rule.

Parts of this chapter have been published in Water [Myo Lin et al., 2018].

4.1. INTRODUCTION

Nowadays, the number of reservoirs in the world is growing in order to meet water and energy demands [Altinbilek, 2002]. Reservoirs are constructed for various purposes, such as irrigation, hydropower generation, water supply, flood control, recreation and navigation. Managing a multipurpose reservoir is complicated due to conflicting interests among these various objectives [Castelletti et al., 2008]. Moreover, a river basin with more than one reservoir, in series or in parallel, requires a more advanced operational method to coordinate multiple reservoirs and multiple objectives [Seibert et al., 2014]. An -optimization based approach is typically required for optimal operation of a reservoir system to obtain the optimal solutions to support the decision-making process [Lin and Rutten, 2016]. The developments in real-time control of a reservoir system have been extensively explored in past literature and generally focus on optimal operation [Che and Mays, 2015; Galelli et al., 2014; Labadie, 2004] and flood control based on pre-defined operation rules and offline approaches [Mohammadi and Mariño, 1984; Niewiadomska-Szynkiewicz et al., 1996; Wei and Hsu, 2008]. Recently, a proactive and online control strategy, the so-called Model Predictive Control (MPC) approach [Camacho and Bordons, 2007; Tian et al., 2015; Maciejowski, 2000] has been widely applied in water resources management to control various water systems such as irrigation systems [van Overloop, 2006b; Negenborn et al., 2009; Zafra-Cabeza et al., 2011] and, drainage systems [van Overloop, 2006b; van Overloop et al., 2008]. MPC is also used in the operational management of a reservoir system for flood mitigation [Breckpot et al., 2013; Delgoda et al., 2013; Ficchì et al., 2016; Schwanenberg et al., 2015; Tian et al., 2015].

MPC has been applied in the industrial process control since 1970s [García et al., 1989]. MPC is a model-based control method which consists of an internal model and the optimization of control objectives. An internal model is used to predict the system states over a prediction horizon and control actions are determined by solving the optimization problem subject to given constraints. MPC is a predictive control method using the receding horizon principle in which a control problem is optimized over a prediction horizon. The first control action is implemented in every control loop, followed by an update of the system states with the new measurements and, consequently, this control problem is resolved for the next control step. As a result, future states are taken into account in every control step and MPC can result in a higher performance than traditional control approaches, such as feed-back control and feed-forward control [van Overloop, 2006b].

Reservoirs can be used to temporarily store the flood volume during heavy rainfall for flood mitigation at the downstream areas. Releases from reservoirs need to be controlled for an efficient use of reservoir storage in order to minimize peak flows at the downstream river reaches. Breckpot et al. [2013] presented a method to use the buffer capacity of a reservoir for flood mitigation. Reservoir releases were considered as control variables in the optimization processes to avoid the non-linearity in the structure equation. We apply this approach in our study. In recent MPC applications, the water flows along the river reaches are usually simulated by applying either the De Saint-Venant equations [Montero et al., 2013; Xu et al., 2012] or integrator delay models [Niewiadomska-Szynkiewicz et al., 1996; Delgoda et al., 2013]. However, the integrator delay model works for only one point with a given delay time and a cross-section area of a river reach and, it is therefore unsuitable to use for a flood control problem. In this study, the dynamics of a water system are described by using the De Saint-Venant equations.

Delgoda et al. [2013] proposed a method to handle uncertain inflows in a MPC formulation for real-time flood control of two reservoirs. Ficchì et al. [2016] also used the deterministic and ensemble weather forecasts in the application of MPC to improve the management of a four-reservoir system for flood control in the Seine River basin, France. In these studies, MPC is used to control a reservoir system to reduce the flood risk at the downstream river reach. As mentioned previously, a reservoir may be used for multiple purposes which also need to be included in the control approach. Our study aims to apply MPC to a multi-reservoir system with two control objectives, flood mitigation and water conservation. A simulation-optimization framework is developed for real-time operation of a reservoir system. Our case study is based on the Sittaung River Basin in Myanmar, where the current reservoir system needs to be equipped with a more effective operation. This study proposes a real-time optimization-based approach for reservoir operations, with two management objectives. Tested on our study area - the Sittuang river basin, our proposed approach outperforms the current operating rule, in terms of vulnerability and reliability. The approach is a generic one, which can also be applied to other multi-reservoir system.

The paper is organized as follows. Section 2 describes the details of the study area, materials, and methods. Simulation settings and operation scenarios are described in Section 3. In Section 4, the results based on different operation scenarios are presented. Finally, in the discussion and conclusion section, limitations of the method and suggestions for future research are presented.

4.2. MATERIALS

4.2.1. STUDY AREA

The Sittaung river is one of the four major rivers in Myanmar. This river flows from north to south through the south central plain of Myanmar and enters into the Andaman Sea. The study area covers the city of Taungoo and its upstream catchment, incorporating 31 sub-catchments and 11 reservoirs (Figure 4.1). The total catchment area is about 19,244 km^2. Given the fact that Taungoo and its surrounding areas frequently suffer flood-induced inundation, a master plan for multipurpose utilization of the integrated water management of the Sittaung River basin has been developed since 1964 by the Myanmar government with technical assistance from experts of the United Nations [United Nations, 1964]. Based on this plan, a series of reservoirs has been constructed along several tributaries of the Sittaung River for the sake of flood control, irrigation and hydropower generation. However, fluvial floods still occur every few years. For instance, an extreme fluvial flood occurred near the Taungoo city in 2013, resulting in more than 2000 km^2 of flooded agricultural land. Therefore, to make the optimal use of existing water infrastructures to mitigate floods is still one of the main concerns of the local authority. In this study, we consider 11 main reservoirs, each one corresponding to an individual sub-catchment. Their storage capacities and operational purposes, as well as the corresponding catchment areas, are given in Table 4.1.

According to their storage capacities, six reservoirs have a buffering storage larger

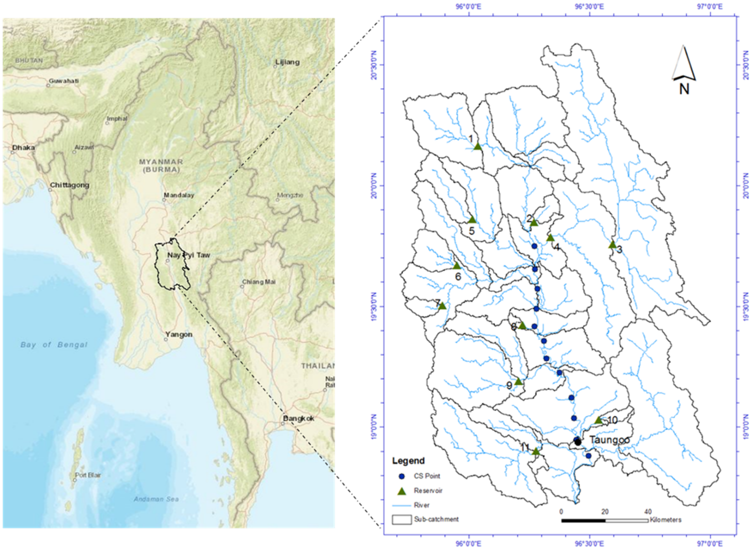

Figure 4.1: Study area — the Sittaung River basin with 11 reservoirs (Salient features of reservoirs are given in Table 1. CS points are the locations where cross-sections were surveyed for this study).

Table 4.1: Reservoirs considered in this study. (Purposes of reservoirs: I=Irrigation, F=Flood control, H=Hydropower).

No.	Reservoir	Catchment Area (km^2)	Storage (10^6m^3)	Max. Capacity (m^3/s) Conduit	Spillway	Purposes I	F	H
1	Sinthe	789	176	15	523	✓	✓	
2	Yezin	91	90	10	23	✓	✓	
3	Upper Paunglaung	3168	1300	100	4000		✓	✓
4	Lower Paunglaung	1551	678	200	3123	✓	✓	✓
5	Ngalaik	328	92	10	400	✓	✓	
6	Chaungmange	265	113	7	74	✓	✓	✓
7	Madam	96	45	8	94	✓		
8	Myohla	28	12	4.25	51	✓		
9	Swa	1053	267	25	1487	✓	✓	
10	Pathi	60	38	3.5	156	✓		
11	Kabaung	1199	1084	40	694	✓	✓	✓
	sum	8628	3895	-	-	10	8	4

Source: Irrigation and Water Utilization Management Department, Myanmar

than 100 Mm^3 to reduce the peak of the flow. Note that each reservoir has two outlet structures, a spillway and a conduit. The spillway is a non-operational free-flowing structure while the conduit is an controllable structure with a vertical gate. The types and characteristics of the spillways are described in Supplementary Materials. The current reservoir operation in the Sittaung River basin is mainly based on water conservation and hydropower generation. In the dry season, the reservoirs are locally operated to meet water demand. During the wet season, the releases are controlled based on hydropower demand and the desired storage of a water supply for irrigation in the dry season. The reservoir operators make release decisions based on the current water levels and the desired water levels without considering the downstream flood risk at Taungoo. Therefore, in addition to conservation of water, an optimal control system is required to reduce potential flood risk in downstream areas.

4.2.2. HYDROLOGICAL AND MORPHOLOGICAL DATA

The hydrological data used in this study, such as rainfall, potential evaporation, water levels and discharges, were collected from the Department of Meteorology and Hydrology (DMH), Myanmar. The hydrological data are limited and only available on a daily resolution. The available rainfall data do not cover the temporal and spatial variation of rainfall across the study area, especially for higher elevation areas. Therefore, the three hourly TRMM (3B42) [Tropical Rainfall Measuring Mission (TRMM) (2011)., 2011] were used for the rainfall-runoff model in this study. The TRMM rainfall data were retrieved from the National Aeronautics and Space Administration (https://mirador.gsfc.nasa.gov). Advantages of TRMM data over other data sets are a better coverage in space and time, and available for near real-time. The information on catchment areas and river system of the Sittaung River basin was derived from the Shuttle Radar Topography Mission (SRTM) 3 arc-second Digital Elevation Model (DEM), which were obtained from the United States Geological Survey (https://lta.cr.usgs.gov/get_data). The key cross-sections (CSs) of the Sittaung River were surveyed for hydrodynamic modelling in 2015 (see Figure 4.1). The CSs of tributaries were generated by using the DEM, channel bed slopes, and Google earth images.

4.3. METHODS

A simulation-optimization framework was developed by using MPC strategy for real-time control of a multi-reservoir system. This framework consists of three main parts: inflow prediction with rainfall-runoff model, real-time control with MPC, and the SOBEK hydrodynamic model. The flow chart of the proposed method is shown in Figure 4.2.

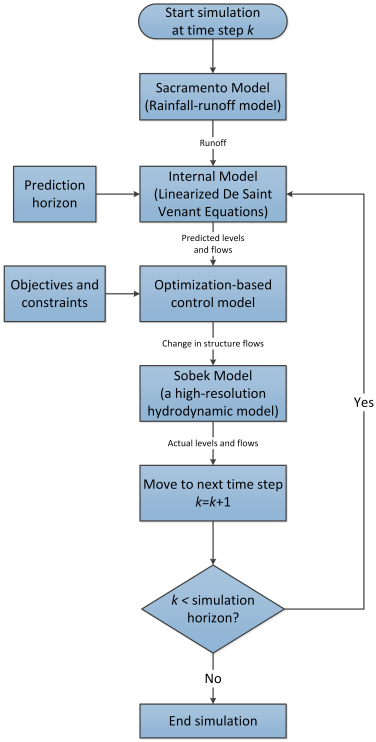

Figure 4.2: Simulation-optimization framework.

4.3.1. Modelling Rainfall-Runoff Process

Rainfall-runoff models are required to estimate outflows of catchments for the optimal operation of a reservoir system. Some well-known rainfall-runoff models include the Hydrologiska Byråns Vattenbalansavdelning model (HBV) [Lindström et al., 1997], the SACramento Soil Moisture Accounting model (SAC-SMA) [Boyle et al., 2001], the Australian Water Balance Model (AWBM) [Boughton, 2004], and the Nedbor Afstromnings Model (NAM) [Nielsen and Hansen, 1973]. In this study, we chose SAC-SMA model due to its satisfactory performance in modelling runoff and the flexibility to be integrated with real-time controllers which we introduce in the subsequent subsection. It is a conceptual hydrological model to estimate the runoff for small to medium-scale catchments. The advantages to use the conceptual model over the physically based model are its simplicity and its ability to save computational time. The key parameters of the SAC-SMA model are a unit hydrograph and soil parameters [Vrugt et al., 2006]. The application of the SAC-SMA model in SOBEK was based on a distributed approach. A catchment was divided into a number of sub-catchments and estimated runoffs of sub-catchments were linked with the main river system. The areas of sub-catchments were ranging from 100 km^2 to 300 km^2. The SAC-SMA model parameters were manually calibrated with observed data. The Nash-Sutcliffe Efficiency (NSE) [Nash and Sutcliffe, 1970] was used to evaluate the model performance. Details of the modelling process are described in Supplementary Materials.

4.3.2. SIMPLIFIED INTERNAL MODEL

In this study, we adopted the MPC approach for real-time control of a multi-reservoir system. MPC incorporates an internal model, an objective function and the constraints. A simplified internal model with a large grid size and large time step were used in this study to achieve computational efficiency. Our simplified model is composed of 82 river reaches and 11 reservoirs (see Figure 4.3).

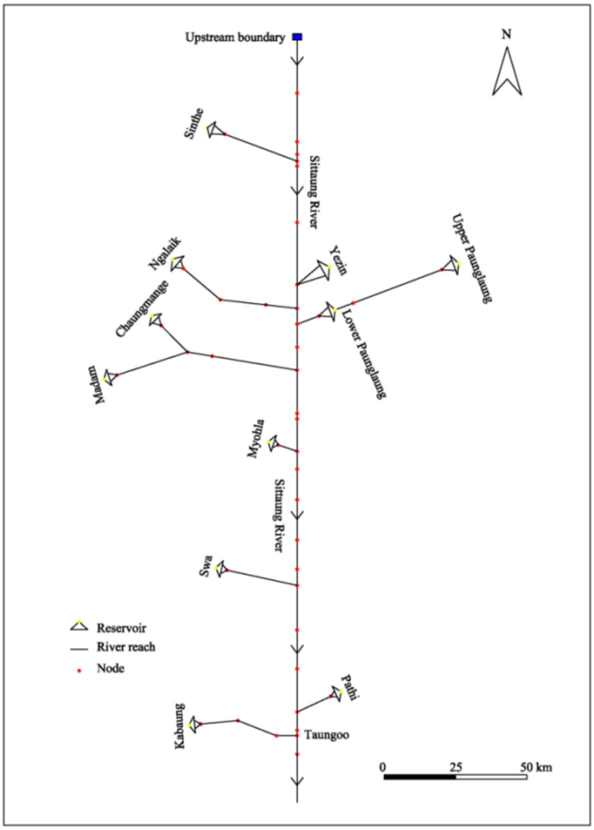

Figure 4.3: A schematic diagram of the simplified internal model.

In this study, the changes of storage in reservoir was modelled by using the following mass balance equation:

$$V_i(k+1) = V_i(k) + \left[Q_{i,d}(k) - Q_{i,s}(k) - \left(Q_{i,g}(k-1) + \Delta Q_{i,g}(k)\right)\right]\Delta t \tag{4.1}$$

$$\Delta Q_{i,g}(k) = Q_{i,g}(k) - Q_{i,g}(k-1) \tag{4.2}$$

where V_i = storage volume of reservoir (m^3), $Q_{i,d}$= inflow to reservoir (m^3/s), $Q_{i,s}$= outflow from the spillway (m^3/s), $Q_{i,g}$ = outflow from the conduit (m^3/s), k= time step index, and Δt= time interval between time step k and $k+1$. The losses from a reservoir (e.g. evaporation and seepage) and the precipitation over a reservoir surface area were neglected for simplification in Equation 4.1. In general, the flow from a spillway or a sluice gate can be a free flow or a submerged flow according to the downstream water level conditions [35]. In the Sittaung river basin, spillways and conduits for all reservoirs were designed for free flow condition. Following van Overloop [2006b], the structure flow can be calculated by using the following linearized structure equations. Free over flow from spillway with fixed crest is determined by:

$$Q_{i,s}(k+1) = Q_{i,s}(k) + C_{i,g}W_{i,g}\sqrt{\frac{2}{3}g\left(h_{i,up}(k) - h_{i,cr}\right)}\Delta h_{i,up}(k) \tag{4.3}$$

4

And also free flow from conduit is calculated by:

$$\begin{aligned} Q_{i,g}(k+1) &= Q_{i,g}(k) + \frac{gC_{i,g}W_{i,g}\mu_{i,g}\left(h_{i,g}(k)-h_{i,cr}\right)}{\sqrt{2g\left(h_{i,up}(k)-\left(h_{i,cr}+\mu_{i,g}\left(h_{i,g}(k)-h_{i,cr}\right)\right)\right)}}\Delta h_{i,up}(k) \\ &+ \left(\begin{array}{l} C_{i,g}W_{i,g}\mu_{i,g}\sqrt{2g\left(h_{i,up}(k) - \left(h_{i,cr} + \mu_{i,g}\left(h_{i,g}(k) - h_{i,cr}\right)\right)\right)} \\ -\frac{gC_{i,g}W_{i,g}\left(h_{i,g}(k)-h_{i,cr}\right)}{\sqrt{2g\left(h_{i,up}(k)-\left(h_{i,cr}+\mu_{i,g}\left(h_{i,g}(k)-h_{i,cr}\right)\right)\right)}} \end{array}\right)\Delta h_{i,g}(k) \end{aligned} \tag{4.4}$$

where Q= flow through structure (m^3/s), C_g = calibration coefficient, W_g= width of the structure (m), μ_g = contraction coefficient, h_{up}= upstream water level (m), h_{cr}= crest level of structure (m), and h_g = gate height (m). Then, the water level at a reservoir is given by:

$$h_i^R(k+1) = h_i^R(k) + \frac{\Delta t}{A_i^R(k)}\left[Q_{i,d}(k) - Q_{i,s}(k) - \left(Q_{i,g}(k-1) + \Delta Q_{i,g}(k)\right)\right] \tag{4.5}$$

where h_i^R= water level at reservoir (m) and, A_i^R= surface area of reservoir (m^2). The desired water level at reservoir is denoted as $h_{i,ref}^R$, then the deviation between reservoir water level and set point, $e_i^R(k+1)$ can be expressed by:

$$e_i^R(k+1) = h_i^R(k+1) - h_{i,ref}^R \tag{4.6}$$

As mentioned above, the water levels and the water flows of the river reaches were simulated by using the one-dimensional De Saint-Venant equations [Chow, 1959], i.e. mass balance and momentum balance equations. Several methods are available to discretize these equations in time and space [Montero et al., 2013; Stelling and Duinmeijer, 2003; Moukalled et al., 2016]. In this study, the staggered grids and implicit integration scheme given by Xu [Xu, 2013] was adapted to discretize the De Saint-Venant equations and resulted the discretized solutions of water levels and flows of river reaches. Then, the deviation between water level and set point at a river reach can be determined by:

$$e^P(k+1) = h^P(k+1) - h_{ref}^P \tag{4.7}$$

where e^P = water level deviation at river reach P (m), h^P = water level at river reach P (m), and h^P_{ref} = flood limit water level at river reach (m). A linear state space model was used in this study. The conduit outflow was chosen as a controlled variable in optimization process to avoid the model complexity because of non-linearity in the structure equation. As one of the operational objectives is to minimize the downstream flood risk, the water levels and structure outflows were taken as the states of the system. The general state space representation of the system was given by:

$$Z(k+1) = A_z(k)\,Z(k) + B_u(k)\,U(k) + B_d(k)\,D(k) \tag{4.8}$$

where the state $Z(k)$ is composed of the water level $h(k)$, the conduit outflow and the water level deviation $e(k)$, i.e. $Z(k) = \left[h(k), Q_g(k), e(k)\right]^T$ is composed of the control variable, i.e. $U(k) = \left[\Delta Q_g(k)\right]$. The disturbance $D(k)$ is composed of the inflow disturbance $Q_d(k)$ and the spillway outflow $Q_s(k)$, i.e. $D(k) = [Q_d(k), Q_s(k)]^T$. $A(k)$, $B_u(k)$ and $B_d(k)$ are the system input matrixes for state, control and disturbance respectively. The elements of these matrixes can be found in Xu [2013].

4

4.3.3. OBJECTIVE FUNCTION AND CONSTRAINTS

In this study, an objective function is defined to minimize the deviations of the water level from the set point and the changes of release from the conduit. The constraints are storage capacities of reservoirs, water demand for hydropower generation and, release capacities of the conduits and spillways. A general from of an objective function used in this study is given by:

$$\min J = Z^T W Z + U^T R U \tag{4.9a}$$

subject to

$$Z^{\min} \le Z(k) \le Z^{\max} \tag{4.9b}$$

$$U^{\min} \le U(k) \le U^{\max} \tag{4.9c}$$

where W and R are weighted matrices which can be defined as the relative importance of sub-objectives in the optimization process. In this study, the Maximum Allowed Value Estimate (MAVE) was used to define the relative penalties to the variables (see more details in van Overloop [2006b]). The objective function is quadratic and the constraints are linear, then this type of an optimization problem can be solved by using quadratic programming. In this study, the interior-point method was used to solve the optimization problem. The details of objective function and constraints will be described in Section 4.4.

4.3.4. MODELLING THE SITTAUNG RIVER SYSTEM

Several software packages are available for hydrodynamic modelling of a river system, such as SOBEK [Tian et al., 2015], TUFLOW [Banks et al., 2014], HEC-RAS [Horritt and

Bates, 2002] and MIKE 11 [Ngo et al., 2007]. Among of the available tools, SOBEK was selected for modelling the Sittaung River system because its ability to integrate rainfall-runoff module, hydrodynamic module, and user-defined routines. SOBEK is a hydrodynamic software package for one dimensional (1D) and two dimensional (2D) flow simulation [Deltares, 2016]. The Sittaung River system was modelled with the SOBEK software package coupled with SAC-SMA rainfall runoff modules. The key parameter considered in this study was the roughness coefficients which were determined through the model calibration. In this study, SOBEK was considered as a real water system and the hydraulic parameters of a simplified internal model were calibrated by SOBEK. This model was also used to update the system states of the simplified internal model. The modelling process is described in Supplementary Materials.

4.4. SIMULATION SETTINGS AND OPERATION SCENARIOS

During high flow periods, the presence of the available storage capacity can be used for the flood mitigation. The developed control system was tested with three operation scenarios using the most severe flood event in 2013. The return period of this flood event is 50 years. The danger water level of the control point (i.e. Taungoo in Figure 4.1) defined by DMH is 43 m. In this study, the safety level was set to 42 m to use the buffer capacities of the reservoirs in advance. The model was simulated with 30 minutes discrete time steps. The control time step was 3 hours with a prediction horizon of 2 days. Firstly, the initial water levels of the reservoirs were set up using the observed data. Several reservoirs (i.e. Lower Paunglaung, Swa and Pathi) were already full in the initial stage. The following operation scenarios were considered in this study.

Scenario 1 (Current operation): Regulation is based on current operating rule in the study area. The SOBEK hydrodynamic model was simulated by using the observed outflow data of the reservoirs.

Scenario 2 (Flood control): Regulation is based on the use of available storage of reservoirs during high inflow events. Releases from reservoirs are controlled with MPC controller based on safety level at a downstream control point. The reservoirs releases water to create the buffering storages for incoming flow when the water level at a control point is lower than the safety level. The conduit gates are closed by the controller when a flood is occurring at the downstream areas. Soft constraints are used to avoid the non-feasibility problem in optimization processes. The deviations of the virtual state outside of the allowed range is denoted as e^{P^*}. The virtual signal, μ^*, is used as a soft constraint to make the virtual state either zero or a value near the allowed range [van Overloop, 2006b].

$$e^{P^*}(k) = h^P(k) - \mu^*(k) \tag{4.10}$$

For this operation scenario, equation (9) can be written as follows:

$$
\begin{aligned}
\min J = & \sum_{j=1}^{N_P} \left[e^P (k+j|k)^T W^P e^P (k+j|k) \right] \\
+ & \sum_{j=1}^{N_P} \left[e^{P*} (k+j|k)^T W^{P*} e^{P*} (k+j|k) \right] \\
+ & \sum_{j=1}^{N_P} \left[\mu^* (k+j|k)^T R_\mu \mu^* (k+j|k) \right] \\
+ & \sum_{j=1}^{N_P-1} \sum_{i=1}^{L} \left[\Delta Q_{i,g} (k+j|k)^T R_{Q_{i,g}} \Delta Q_{i,g} (k+j|k) \right]
\end{aligned}
\tag{4.11a}
$$

subject to

$$
Q_{i,g}(k) = \begin{cases} 0 & if\ h_i^R(k) \le h_i^{R,D} \\ 0 \le Q_{i,g}(k) \le Q_{i,g}^{max} & if\ h_i^R(k) > h_i^{R,D} \end{cases} \tag{4.11b}
$$

$$
0 \le Q_{i,s}(k) \le Q_{i,s}^{max} \tag{4.11c}
$$

$$
\mu^*(k) = \begin{cases} h^P(k) & if\ h^P(k) \le h_{SL}^P \\ h_{SL}^P & if\ h^P(k) > h_{SL}^P \end{cases} \tag{4.11d}
$$

$$
V_i^D \le V_i(k) \le V_i^{max} \tag{4.11e}
$$

where $h_i^{R,D}$= dead storage level at reservoir i (m), $Q_{i,g}^{\max}$= maximum conduit outflow at conduit i (m^3/s), $Q_{i,s}^{\max}$= maximum spillway outflow at spillway i (m^3/s), h^P= water level at river reach P (m), h_{SL}^P= safety level at river reach P (m), V_i^D = dead storage capacity at reservoir i (m^3), $V_i^{\max}$= maximum storage capacity at reservoir i (m^3), and N_P= prediction horizon (hour).

Scenario 3 (Conservation and flood control): MPC is used to control the desired storage capacity of reservoirs for the dry season and flood mitigation at the downstream river reaches. An objective function is set up to control the water levels of reservoirs under given constraints. The minimum releases from reservoirs are used as the hard constraints for hydropower demand and a soft constraint on safety level is used for flood mitigation at a downstream control point. For operation scenario 3, Equation 4.9 can be written as follows:

$$
\begin{aligned}
\min J = & \sum_{j=1}^{N_P} \sum_{i=1}^{L} \left[e_i^R (k+j|k)^T W_i^R e_i^R (k+j|k) \right] \\
+ & \sum_{j=1}^{N_P} \left[e^{P*} (k+j|k)^T W^{P*} e^{P*} (k+j|k) \right] \\
+ & \sum_{j=1}^{N_P} \left[\mu^* (k+j|k)^T R_\mu \mu^* (k+j|k) \right] \\
+ & \sum_{j=1}^{N_P-1} \sum_{i=1}^{L} \left[\Delta Q_{i,g} (k+j|k)^T R_{Q_{i,g}} \Delta Q_{i,g} (k+j|k) \right]
\end{aligned}
\tag{4.12a}
$$

subject to

$$Q_{i,g}(k) = \begin{cases} 0 & if\ h_i^R(k) \le h_i^{R,D} \\ Q_{i,g}^{\min} \le Q_{i,g}(k) \le Q_{i,g}^{max} & if\ h_i^R(k) > h_i^{R,D} \end{cases} \tag{4.12b}$$

$$0 \le Q_{i,s}(k) \le Q_{i,s}^{max} \tag{4.12c}$$

$$\mu^*(k) = \begin{cases} h^P(k) & if\ h^P(k) \le h_{SL}^P \\ h_{SL}^P & if\ h^P(k) > h_{SL}^P \end{cases} \tag{4.12d}$$

$$V_i^D \le V_i(k) \le V_i^{max} \tag{4.12e}$$

where = number of reservoirs.

4

4.4.1. Performance Indicators

One of the control objectives is to refill the storage of reservoirs during the wet season to assure water demand for the dry season. Wei and Hsu [2009] introduced criteria for a reservoir target storage meeting rate as follows:

$$S = \sum_{i=1}^{L} \left[\frac{S_i^{end}}{S_i^{target}} \right] \tag{4.13}$$

where S = reservoir storage capacity meeting rate (%), S^{end} = reservoir storage capacity at end of simulation (m^3), and S^{target} = targeted reservoir storage capacity (m^3). Flood damages depend on the inundation depth, duration and land use of the flooded area. A higher water level endangers the local population. In this study, the system vulnerability was defined with the water depth above the danger water level.

$$F = \begin{cases} \frac{h_{max} - h_{dl}}{h_{dl}} & h_{max} \ge h_{dl} \\ 0 & h_{max} < h_{dl} \end{cases} \tag{4.14}$$

where F = vulnerability (%), $h_{\max}$ = maximum water level occurring at a control point (m), h_{dl} = danger water level at a control point (m). One of the important factors for flood risk management is the flood duration as a measure of the system resilience. McMahon et al. [2006] defined system resilience based on the failure duration as follows:

$$R = \frac{N}{\sum_{j=1}^{N} (D_j)} \tag{4.15}$$

where R = system resilience (%), D_j = flood duration of event in which the water levels reach above danger level (hour), N = number of continuous flood events.

4.5. Results

The NSE value of the daily mean water levels at the Taungoo gauge station is 0.76 and the model is able to estimate the water levels and flows of the Sittaung River system. The model output was compared for the different operation scenarios. Figure 4.4 shows the outflow and water levels of the selected reservoirs for the different operation scenarios.

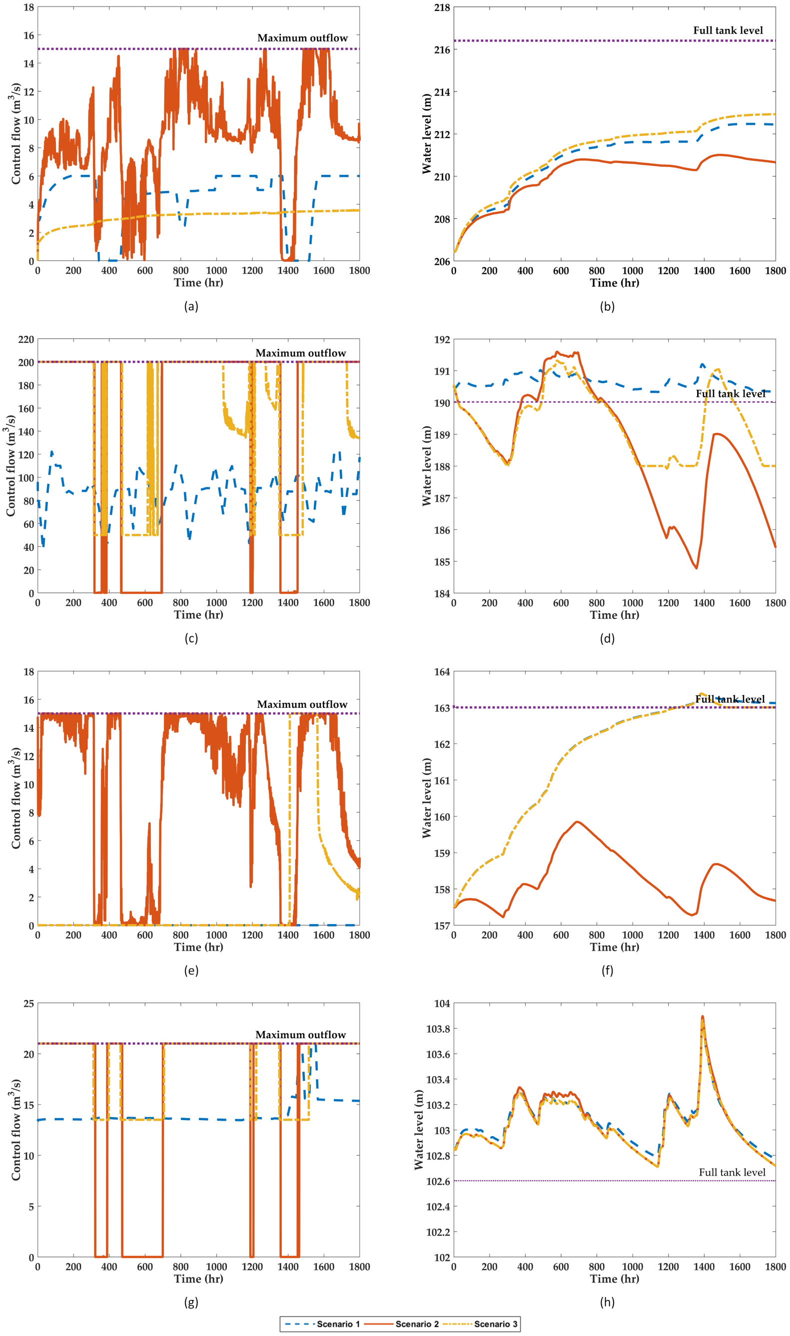

Figure 4.4: Control flows and water levels with respect to three operation scenarios based on four selected reservoirs: (a, b) Sinthe reservoir; (c, d) Lower Paunglaung reservoir; (e, f) Ngalaik reservoir; and (g, h) Swa reservoir.

The controlled outflow from the Sinthe reservoir are shown in Figure 4.4(a). For scenario 1, the releases were based on the current operation rule. In scenario 2 , the controller released more water to create a storage space for flood regulation at Taungoo; the conduit gate was closed when the water level reached above the safety level. In scenario 3, the reservoir released the minimum demand for conservation and stored the water for irrigation in dry season. The water level changes of the Sinthe reservoir are shown in Figure 4.4(b).

The Lower Paunglaung reservoir was used for multiple purposes. This reservoir was full and released water at the initial stage of the simulation. The reservoir released water for hydropower demand in scenario 1 (Figure 4.4(c)). The current reservoir operation was based on the local condition (i.e. water demand for hydropower and desired storage for the dry season) without considering the risk of a downstream flood. For scenario 2, the conduit gate was fully opened, creating a storage space for high inflow and the controller closed the gate to maintain desired water level (safety level) at the control point. In scenario 3, the controlled water level was set to 189 m to store water for the dry season and the minimum outflow was used as a hard constraint for hydropower demand. A high penalty was used for violations of soft constraint in flood control objective and therefore the reservoir released the minimum outflow during floods.

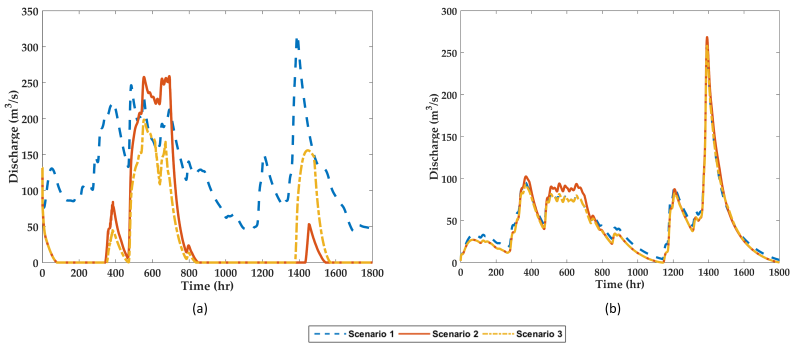

Figure 4.5: Significant releases from the uncontrolled spillways: (a) Lower Paunglaung reservoir and (b) Swa reservoir.

The Ngalaik reservoir is mainly used for irrigation and recreation during the dry season. Therefore, the main operation objective is that the reservoir needs to be full at the end of wet season. It was full at the end of the simulation when the operation was based on scenario 1 and 3 (Figure 4.4(f)). For scenario 1, there was no outflow from the reservoir to store the water for conservation purposes in the dry season (Figure 4.4(e)). For scenario 3, the reservoir release was controlled to keep the water level at its full tank level (i.e. 163 m). The final storage capacity was reduced to 45% when we considered the regulation based on flood priority in scenario 2.

The Swa reservoir showed a similar performance as compared to the other reservoirs (Figure 4.4(g, h)). At the initial stage, the reservoir water level exceeded its full tank level and the uncontrolled releases occurred through the reservoir spillway. For the flood regulation in scenario 2, the controller opened or closed the conduit gate based on the desired water level at the control point. Even though maximum releases were made during the operation, the reservoir water level could not be reached under a full tank level. Due to the limitation on the outlet capacity, the conduit gate was not able to release a large quantity of water in advance to get the desired water level in the reservoir. The significant releases from two spillways are shown in Figure 4.5. The spillway releases also contributed to increase the water depth at Taungoo city by releasing 25% of peak discharge during this flood event.

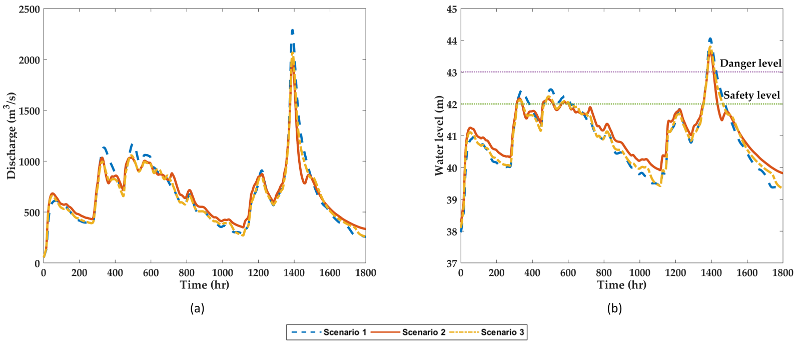

Figure 4.6: Simulation results at Taungoo with respect to three operation scenarios: (a) Discharge and (b) water levels.

Table 4.2: Overall performance of the three operation scenarios.

Indicators	Operation scenarios		
	1 (Current operation)	2 (MPC-Flood priority)	3 (MPC-Conservation priority)
Storage volume (%)	**87**	67	86
Vulnerability (%)	2.4	**1.5**	1.8
Resilience (%)	1.9	**2.8**	2.4

In this study, a centralized control system was developed for flood control at a downstream river reach. The simulation results at Taungoo (i.e. flood control point) are shown in Figure 4.6. Under the operation scenario 1, the water level exceeded 1.09 m above its danger level at Taungoo. In scenario 2, the reservoirs' releases were controlled by MPC to maintain a water level lower than the danger level at a control point. Even though, MPC worked well to control the reservoir releases, violations could not be avoided during high inflow due to the inflow from uncontrolled catchments and the limitations of the reservoir storages and conduit gate capacities. However, under this operation the peak water level was reduced to 40 cm. The operation based on flood priority is not always optimal when reservoirs are used for multiple purposes. Therefore, we considered the optimal operation in scenario 3. Consequently, an objective function was set up with a desired storage capacity and a minimum release for each reservoir and a soft constraint on water level violation was used for the flood control at a downstream river reach. The peak water level at the control point was reduced to 30 cm under operation of scenario 3. It was obvious that the flooding was not only caused by the releases from the reservoirs, but also by the inflow from the uncontrolled catchments.

The overall performance of the three operation scenarios is shown in Table 4.2 in terms of storage volume, system vulnerability and resilience, described in section 3.6. The highest system vulnerability (2.4%) existed under operation scenario 1 which was based on the current operation setting. In operation scenario 2, MPC was used to optimize reservoir releases to control the water level at Taungoo for flood prevention and the system vulnerability reduced to 1.5%. MPC controller used the buffer capacities of reservoirs to maintain the water level near around the safety level. However, the potential of the flooding was unavoidable due to high inflow from the uncontrolled catchments (i.e. 45% of total catchment). In addition, the releases from uncontrolled spillways also caused the water level to increase at the control point. Operation scenario 3 takes into account the desired storage capacities, water demand and flood prevention in the optimization problem. A risk of water shortage in scenario 2 operation was recovered (from 67% to 87%) under operation scenario 3. However, flood risk was increased under this operation compared to scenario 2. The simulation result indicates that system vulnerability could be reduced from 2.4% to 1.5% by creating the storage spaces under the MPC operation. Among 11 reservoirs in the system, Upper Paunglaung, Lower Paunglaung, Swa and Kabaung are important reservoirs for the flood control operation as these reservoirs have significant storage capacities and outlet capacities.

4.6. Discussion

This study focused on the implementation of MPC in a large-scale water system and on flood risk mitigation in the Sittaung River basin, Myanmar. The optimization formulation in MPC was based on a deterministic disturbance to examine the flood mitigation capacities of the existing reservoirs for a severe flood event. The satellite rainfall data were used to estimate the outflows from the sub-catchments. Regarding with rainfall-runoff model, the buffer capacities of existing reservoirs are overestimated if inflow into the system is underestimated. On the other hand, the buffer capacities of existing reservoirs are underestimated if inflow into the system is overestimated. For this reason, it is required to communicate uncertainty associated with inflow prediction. This issue could be overcome by using MPC with the ensemble forecast [Raso, 2013; Uysal et al., 2018]. In addition, we assumed that SOBEK represents an actual water system and the water levels of a simplified model were updated with the water levels from SOBEK. Therefore, the effect of measurement noises should also be considered in a real-world operation.

In the MPC formulation, it is important to use a proper prediction horizon (N_P). The computational time increases when using a longer prediction horizon. Although Np increases, it does not guarantee to have a better model performance because it is also dependent on capacities of the system [Tian et al., 2017]. On the other hand, especially for a water system with delays, Np should not be smaller than the delay time. Otherwise, several control inputs might not affect any of the system outputs. At present, only a three-day weather forecast with a chance of rain is available for the cities in the study area at the DMH website (www.moezala.gov.mm). In addition, the travel time of outflow from the furthest reservoir (i.e. Sinthe reservoir) is around 41 hours for the mean flow. Based on these facts, the length of the prediction horizon was chosen as 2 days which could capture the dynamics of the Sittaung river system. If the reservoirs have full storage capacities before a flood occurs, most of the reservoirs require more than 90 days to completely empty their water storages. In fact, the constraints on the conduit capacities play an important role to reduce the flood risk in the Sittaung river basin.

In this study, we applied a weighted approach and a constrained approach to operate a multi-reservoir system. In operation scenario 2, we considered two control objectives, minimization of water level deviations from set point and changes in reservoir releases. The weights were defined by using MAVE and this solution depended on given weights. In operation scenario 3, we optimized the storage capacities of the reservoirs and constraints were used to satisfy two other control objectives, i.e. flood control and hydropower generation. Improving the decision-making process, a pareto optimal approach is preferred for trade-off between two or more conflicting objectives (i.e. desired storage capacity, hydropower generation and flood prevention). Recently, the Multi-Objective Evolutionary Algorithm (MOEA) is widely applied for the multi-objective optimization of water systems [Chiang and Willems, 2015; Chang and Chang, 2009; Reddy and Kumar, 2006]. However, it is still required to explore the application of MOEA in a MPC scheme because of its computational efficiency. Therefore, it would be interesting to adapt this method to analyze the trade-off between conflicting objectives in real-time reservoir operation under MPC strategy.

As mentioned above, one of the limitations of this study is the rainfall-runoff model is case specific. To apply the proposed approach to other study area, the real-time control approach needs to be coupled with new rainfall-runoff models. However, the control approach is generic. Besides, the methodology is not suitable for problems with predictions longer than one week. In fact, the computational complexity increased in a cubic order of the problem size and the accuracy of predictions also decreases as the prediction becomes longer. But this issue is acceptable at this step as most real-time control problems adopt two days as the length of the prediction.

4.7. CONCLUSIONS

This paper demonstrates the performance of MPC on the flood control of a complex river system which is composed of multipurpose reservoirs and uncontrolled sub-catchments. A centralized control system was developed and tested with three operation scenarios. A comparison between MPC operation and the current operation was presented, resulting in a reduction of the system vulnerability by 0.9% under the operation scenario 2 compared to the operation scenario 1. However, the total storage volume was reduced from 87% to 67% and water shortage would occur in the dry season. Thus, a third scenario was developed in which water levels of the reservoirs (i.e. desired storage volume) were set up as the main control objective to maintain the desired storage volume, considering minimum demands as hard constraints and safety water level at a flood control point as a soft constraint. For scenario 3, the results indicate an improvement in the operation of multi-objectives compared to the other two scenarios. In this study, the minimum releases were used as the hard constraints for hydropower production. Therefore, future study needs to take into account the maximization of energy production in the optimization processes to make a trade-off between multiple objectives. In facts, it is impossible to completely eliminate the flood risk at Taungoo city due to limitations on the capacities of the structures. However, the results indicate that the potential flood risk can be reduced by improving the current reservoir operating rule.

5

Multi-objective Model Predictive Control for Real-time Operation of a Multi-Reservoir System

This chapter presents an extended Model Predictive Control scheme called Multi-objective Model Predictive Control (MOMPC) for real-time operation of a multi-reservoir system. The MOMPC approach incorporates the non-dominated sorting genetic algorithm II (NSGA-II), multi-criteria decision making (MCDM) and the receding horizon principle to solve a multi-objective reservoir operation problem in real time. In this study, a water system is simulated using the De Saint Venant equations and the structure flow equations. For solving multi-objective optimization, NSGA-II is used to find the Pareto-optimal solutions for the conflicting objectives and a control decision is made based on multiple criteria. Application is made to an existing reservoir system in the Sittaung river basin in Myanmar, where the optimal operation is required to compromise the three operational objectives. The control objectives are to minimize the storage deviations in the reservoirs, to minimize flood risks at a downstream vulnerable place and to maximize hydropower generation. After finding a set of candidate solutions, a couple of decision rules are used to access the overall performance of the system. In addition, the effect of the different decision-making methods is discussed. The results show that the MOMPC approach is applicable to support the decision-makers in real-time operation of a multi-reservoir system.

Parts of this chapter have been published in Water [Myo Lin et al., 2020].

5.1. INTRODUCTION

Reservoirs are important water retaining structures for management and sustainable development of the world's water resources. At present, though the social and environmental impacts of dams is being debated, more than 50,000 large dams have been constructed worldwide for irrigation, hydropower generation, flood control, navigation and recreation [Lehner et al., 2011]. According to the report of the world commission on dams, [WCD, 2000], the improvement in operation and maintenance of existing dams offer opportunities to address local (or) regional developments and to minimize the social and environmental impacts. Over the past decades, many researchers have emphasized the optimal operation of a multi-reservoir system for long-term planning [Castelletti et al., 2014; Ehsani et al., 2017], developing operating rules [Oliveira and Loucks, 1997; Lund and Ferreira, 1996] and real-time operations [Tian et al., 2015; Myo Lin et al., 2018]. Nowadays, many existing reservoirs are threatened by a changing climate and by growing demands for freshwater and electricity and thus real-time operation plays an important role in reservoir management to improve the performances of existing reservoirs using real-time information such as water demand, rainfall, water level and flow measurement.

In general, optimization, simulation and combined optimization–simulation approaches have been commonly applied to reservoir operation studies. Regarding the optimization techniques, linear programming (LP) and dynamic programming (DP) are mostly used to find the optimal releases of reservoirs [Becker and Yeh, 1974; Needham et al., 2000; Wei and Hsu, 2008; Li et al., 2014]. Among them, LP is suitable for a linear optimization problem that consists of a linear objective function subject to linear constraints. DP is more popular than LP because its ability to deal with nonlinearity and stochastic features [Yeh, 1985]. However, for a large-scale reservoir system, DP suffers from dimensionality problem that is exponential growth of the states and control variables when the number of reservoirs in the system is increased [Castelletti et al., 2008; Wasimi and Kitanidis, 1983]. Although NLP can deal with non–separable objective functions and nonlinear constraints, it is much more complicated and takes time to solve the optimization process compared with the other methods [Yeh, 1985]. In the past, many studies have focused on improving the optimization techniques for the optimal operation of a reservoir system [Cervellera et al., 2006; Li et al., 2014; Needham et al., 2000; Yeh and Becker, 1982]. On the other hand, simulation models have also been used to analyze the performance of a reservoir system under alternative operating policies [Joshi and Gupta, 2009; Seibert et al., 2014; Sigvaldson, 1976]. Hydrologic or hydraulic routing method is commonly used to model a water system involving reservoirs, hydraulic structures and channels. The most effective approach for solving reservoir operation problems is a combination of optimization and simulation model [Fayaed et al., 2013; Lin and Rutten, 2016; Ngo et al., 2007] in which the control decisions are made by optimizing the control objectives and a simulation model is used to estimate the response of the system for certain control decisions. At present, various combinations of optimization–simulation models are available for real-time operations of a reservoir system and the choice of a method depends on the characteristic of a certain reservoir system, for example, number of reservoirs, types of objective functions and constraints.

In recent years, an advanced real-time control method, the so-called Model Predictive Control (MPC) has been widely applied in water resources management to solve various problems [Abou Rjeily et al., 2018; Maestre et al., 2013; van Overloop et al., 2010; Sankar et al., 2015]. In fact, MPC is also promising for real-time operations of a reservoir system because it is based on an optimization–simulation approach and is not limited for the various practical application in terms of process model, objective function and constraints [García et al., 1989; Lin and Rutten, 2016]. MPC differs from the available methods such as a combined DP-LP approach [Becker and Yeh, 1974], linear quadratic gaussian control [Wasimi and Kitanidis, 1983] and simulation and optimization modelling approach [Ngo et al., 2007] because it anticipates the future system states by optimizing the control objectives along a prediction horizon subject to the system constraints, however, only the first control action is implemented to the system at every control step. Subsequently, the system is updated with the new measurements and the optimization is repeated at each time step [van Overloop, 2006b]. MPC is a model-based control technique that involves an internal model to predict the system states, optimization of the control objectives along a prediction horizon subject to the system constraints and the use of receding horizon principle [Camacho and Bordons, 2007]. Recently, increasing attention has been given to the use of MPC in real-time reservoir operations for various purposes; for example, flood control [Delgoda et al., 2013; Ficchì et al., 2016], optimal reservoir operation [Galelli et al., 2014; Myo Lin et al., 2018] and a combination of short and long-term reservoir management [Raso and Malaterre, 2017].

Delgoda et al. [Delgoda et al., 2013] proposed the adaptive multi MPC for flood control of a single reservoir, in which inflow uncertainty was addressed using independent MPC controllers and Kalman filters. Using the transport delay in the process model, it has the challenges to capture the dynamics of a large-scale water system. Another way of dealing with forecast uncertainty in the MPC formulation is to use ensemble forecast data to generate the disturbance scenarios or trees that allow to find the adaptive control actions through forecast uncertainty [Raso et al., 2014; Tian et al., 2017; Uysal et al., 2018]. Regarding multi-purpose consideration, Galelli et al. [Galelli et al., 2014] presented a deterministic MPC scheme for the optimal operation of the Marina reservoir in Singapore that addressed the trade-offs between flood control, pump usage, and drinking water supply. In addition, Raso et al. [Raso and Malaterre, 2017] proposed an infinite horizon MPC using input structuring to reduce the computational complexity in the optimization process which enables to use MPC in long-term optimal reservoir operation. Other developments, MPC combined with the ensemble forecasts for a single reservoir management, can be found in [Schwanenberg et al., 2015; Raso et al., 2014]. For a basin scale, Ficchì et al. [Ficchì et al., 2016] applied MPC and tree-based MPC (TB-MPC) for flood operation of a four-reservoir system in the Seine River basin (France) and compared the performance of MPC based on a perfect forecast, a deterministic forecast and the ensemble forecast. Although TB-MPC is able to improve the performance of the system, its computational time is 7 times larger than the deterministic MPC and could be increased by adding new reservoirs. In order to reduce the computational time, Tian et al. [Tian et al., 2015] proposed a large time step scheme to control a large-scale water system, in which a simplified internal model with the large time step setting was used. This simplified model is based on the De Saint Venent equations and has an ability to solve the control process in a reasonable time. Myo lin et al. [Myo Lin et al., 2018] also applied a simplified internal model to develop an efficient MPC scheme for the optimal operations of the eleven reservoirs in the Sittaung river basin, Myanmar. Over the past decades, most of the studies have focused on flood operation and how to deal with inflow uncertainty in the MPC formulation. On the other hand, multi-reservoir operations may involve multiple conflicting objectives and thus it is required to address the trade-offs between them concerning the decision-maker's preferences.

The above MPC formulations employ either a weighted-sum or a constraint method to solve the multi-objective control problems, using quadratic programming or nonlinear programming. These classical methods transform a multi-objective optimization problem into a single-objective optimization problem and aim to find one particular trade-off solution at a time. However, multiple trade-off solutions, also known as the Pareto-optimal solutions that are better than all other solutions in at least one objective, exist in solving a multi-objective optimization problem [Deb, 2014]. Thus, for the classical methods, the repetitive optimization is required to find all possible optimal solutions that is subjective to the decision-making in real time. In recent years, multi-objective evolutionary algorithms (MOEAs) are gaining significant attention for multi-objective optimization due to their ability to solve nonconvex, nonlinear and discontinuous problems [Reed et al., 2013] and to discover the Pareto-optimal solutions between the conflicting objectives as well. The genetic algorithm (GA) is one of the powerful MOEAs that have been widely applied to water resources planning and management problems [Nicklow et al., 2010], such as reservoir operations [Reddy and Kumar, 2006], optimal design of water distribution systems [Fu et al., 2013], optimization of ground water monitoring systems [Reed and Kollat, 2013], planning of a water supply system under deep uncertainty [Kasprzyk et al., 2013] and inter-basin water transfers [Guo et al., 2020]. In the context of MPC, Núñez et al. [Núñez et al., 2014] presented an MPC scheme to solve a dynamic pickup and delivery problem, in which GA was used to find the trade-off solutions between the two conflicting objectives, namely the user cost and the operator cost. Another MPC formulation used GA to operate the hydraulic structures in real-time flood control of a river system [Chiang and Willems, 2015]. Afterwards, Vermuyten et al. [Vermuyten et al., 2018] addressed the computational burden of GA by using the reduced genetic algorithm (RGA) in an MPC formulation in which RGA was used to optimize the gate levels of hydraulic structures for real-time flood Control. This study showed that the convergence rate of RGA was higher than the standard GA. However, a drawback is that the control solutions may be changed by generating random gate level scenarios with same parameter settings in different optimization runs. In addition, Tian et al. [Tian et al., 2019] presented the combination of multi-scenario MPC with GA for operational water management and discussed how to select a solution for implementation using the three performance matrices. A main concern of this method is how to efficiently choose a single optimal solution from a Pareto-optimal set. Furthermore, reservoir operations need to address the conflicting behavior of management objectives, consequences of the different decision criteria and the decision-maker involvement in the decision-making process. Thus, a more efficient MPC scheme is required for real-time operation of a water system that allows the decision-makers to visually evaluate and adjust the future output of a process model online in accordance with the different decision criteria. For this reason, this paper proposes a method, called multi-objective Model Predictive Control

(MOMPC), to operate multiple reservoirs in real time through an extended MPC scheme that incorporates multi-objective optimization, multi-criteria decision-making and a receding horizon principle.

In the proposed MOMPC formulation, the De Saint Venant equations are used to capture the dynamics of a reservoir system and the non-dominated sorting algorithm-II (NSGA-II) developed by Deb et al. [Deb et al., 2002] is adopted to find the Pareto-optimal solutions for the conflicting objectives. As the receding horizon principle is applied, an optimal control sequence is determined along a prediction horizon at every control time step, however, only the first control action is implemented to the system to move the next step [Morari and H. Lee, 1999]. Therefore, the implementation of NSGA-II in MPC formulation requires a decision criterion to choose a preferred solution at every control step. For this task, multi-criteria decision-making (MCDM) techniques are used to choose a preferred solution from a set of Pareto-optimal solutions. Currently, a number of methods are available in the decision-making field and an extensive review of its strengths and drawbacks can be found in [Kumar et al., 2017]. This study employs the three different decision methods to choose a solution from a Pareto-optimal set and discusses the effect of each decision method on the management objectives. The main advantage of this approach is that it is flexible to make a preferred decision through the visualization of multiple trade-off solutions in real-time. In addition, it is less subjective to solve a multi-objective control problem compared to the classical MPC formulation. To show its ability, the proposed method was applied to real-time operation of a multi-reservoir system in the Sittaung river basin, Myanmar.

This paper is organized as follows. In Section 5.2, we present the proposed MOMPC framework in detail. A case study is described in Section 5.3. Thereafter, in Section 5.4, the results are reported, followed by the discussion in Section 5.5. Finally, conclusions are presented in the last section.

5.2. METHODOLOGY

The proposed MOMPC framework combines the non-dominated sorting genetic algorithm (NSGA-II), multi-criteria decision making (MCDM) and the receding horizon principle to operate a multi-reservoir system in real-time. The structure diagram of the method is shown in Figure 5.1.

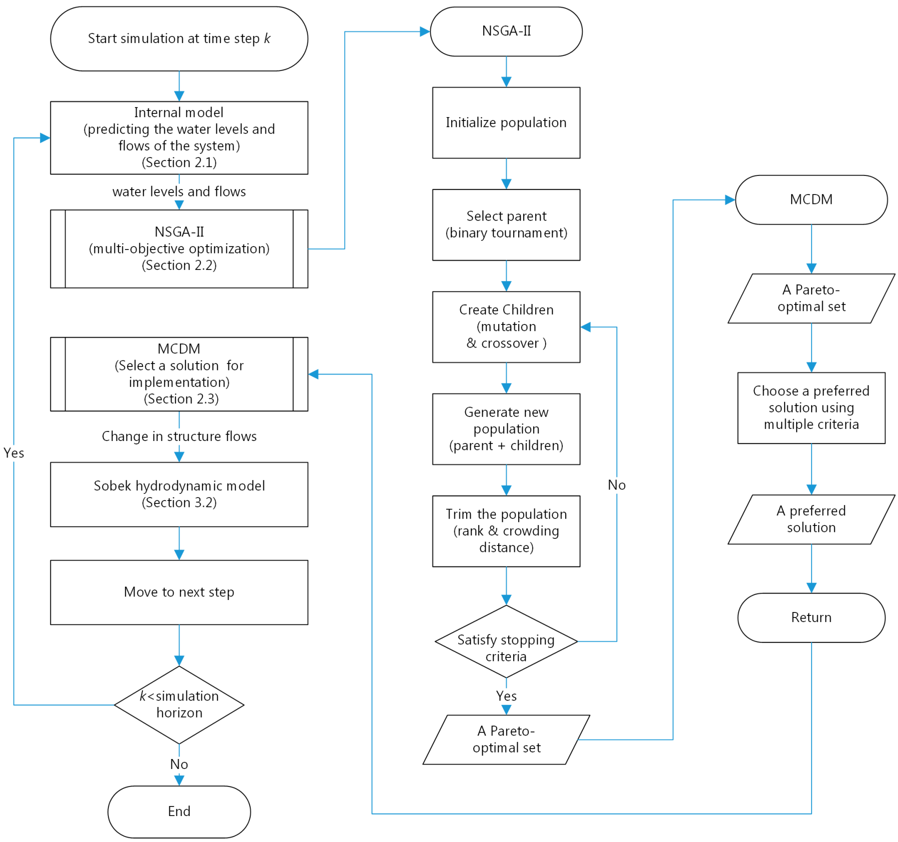

Figure 5.1: The algorithm of multi-objective Model Predictive Control.

5.2.1. Internal Model or Reservoir System Model

In MOMPC formulation, a reservoir system model is required to predict the future water levels and flows of the system over a prediction horizon as a result of predicted inflows and control flows. Generally, the water levels and flows of a river system can be simulated by using the De Saint Venant equations [Chow, 1959]. This model has been widely used as an internal model in MPC formulation to solve various water management problems [van Overloop, 2006a; Breckpot et al., 2013; Tian et al., 2015] and it can capture the basic dynamics of a water system [Xu et al., 2011]. In this study, we employed a simplified internal model used in [Myo Lin et al., 2018; Xu et al., 2012; Tian, 2015] to approximate the water levels and flows of a reservoir system. The state space representation of a controlled reservoir system can be generally described as follows:

$$x^{k+1} = A_x^k x^k + B_u^k u^k + B_d^k d^k \tag{5.1}$$

where the state vector x is composed of the water levels and flows of the system, the input vector u is composed of the controlled releases of reservoirs, the disturbance vector d is composed of inflows into the system and k denotes the discrete time step. A_x, B_u

and B_d are the matrices relating to the successor state with the current state, input and disturbance, respectively, which can be derived from the discretization of the De Saint Venant equations in time and space Xu [Xu, 2013]. In this study, the staggered grids and implicit numerical integration method presented by Stelling and Duinmeijer [Stelling and Duinmeijer, 2003] was adopted to discretize the De Saint Venant equations because of its ability to deal with every Froude number in the shallow water flows.

5.2.2. MULTI-OBJECTIVE OPTIMIZATION

Most real-time operations of multi-reservoir systems involve multiple conflicting objectives, such as irrigation, hydropower generation, flood control and recreation. The demands of these objectives may compete with each other to meet their own management goals. A clear conflict exists between flood control and hydropower generation that flood prevention requires low reservoir water level to create a storage space for large inflow, while high reservoir water level is required for the maximization of hydropower production. During flood event, water supply shortage can be occurred by restriction of reservoir release. In addition, water supply for irrigation, hydropower generation and recreation are competitive each other due to limited storage of reservoir. Clearly, the tasks of reservoir operators are challenging to seek the possible trade-offs between conflicting objectives. The various techniques have been developed to address multi-objective optimization problems and the choice of an optimization method depends on type of problems, available information and the user's preferences [Marler and Arora, 2004]. The commonly used methods are a priori methods such as utility function method, lexicographic method and goal programming, and a posteriori methods such as evolutionary algorithms and normal boundary intersection [Marler and Arora, 2004].

5

MULTI-OBJECTIVE OPTIMIZATION IN THE CLASSICAL MPC

In general, the classical MPC formulation uses a priori methods termed the weighted-sum method to solve a multi-objective control problem as follows:

$$\min J(u) = \sum_{k=1}^{N} w_1 J_1(u_k) + \ldots\ldots + \sum_{k=1}^{N} w_m J_m(u_k) \tag{5.2a}$$

$$J_l(u) = \sum_{k=1}^{N} f_l(x^k, u^k) \tag{5.2b}$$

$$k = 1, \ldots., N, l = 1, \ldots, m$$

subject to

$$x^{k+1} = A_x^k x^k + B_u^k u^k + B_d^k d^k \tag{5.2c}$$

$$x_{i,\min} \leq x_i \leq x_{i,\max} \tag{5.2d}$$

$$u_{i,\min} \leq u_i \leq u_{i,\max} \tag{5.2e}$$

where J = objective cost function, w= weighting factor reflecting the relative importance of J, m =number of objective functions and N= number of prediction steps. In this method, the weight corresponds to the relative important of each objective and the changes in weight vectors will result the different optimal solutions. Without any information of the weight vectors, this method is highly subjective to find an optimal solution. Moreover, the weighted-sum method is not applicable to find all Pareto optimal solutions in a single simulation run [Deb, 2014]. Thus, it is difficult to apply the weighted-sum approach to any problem, and an MOMPC approach is discussed in the next section.

Multi-Objective Optimization in MOMPC

Instead of scalarizing multiple objectives to a single-objective in the classical MPC formulation, MOMPC optimizes multiple objectives to find the Pareto-optimal solutions. In mathematical terms, the reservoir operation problem can be generally expressed as:

$$\min J(u) = \{J_1(u), J_2(u), ..., J_m(u)\} \tag{5.3a}$$

subject to

$$G_a(u) \le 0, \quad c = 1, 2, ..., n_I \tag{5.3b}$$

$$H_b(u) = 0, \quad r = 1, 2, ..., n_E \tag{5.3c}$$

5

where n_I is the number of inequality constraints and n_E is the number of equality constraints. To deal with conflicting objectives, MOMPC uses the same internal model in the classical MPC, however, a multi-objective control problem is solved using NSGA-II to determine a Pareto solution set and an optimal solution is selected with a MCDM method at every control step. NSGA-II proposed by Deb et al. [Deb et al., 2002] is a particular type of multi-objective evolutionary algorithms (MOEAs) that outperforms to find a diverse set of solutions and in achieving better convergence by using elitism approach compared to other MOEAs [Deb et al., 2002]. The first step of NSGA-II is to create the initial populations. For the next generation, parents are selected from the population by using binary tournament selection based on the rank and crowding distance. The selected parents generate the children from mutation and crossover operators. The current parents and current children are sorted again based on the rank and the crowding distance and only the best s individuals are selected. The optimization is terminated based on defined stopping criteria (see in Table 5.1), hence the process is repeated to the next time step. The flowchart of NSGA-II is shown in Figure 5.1. In this way, a Pareto-optimal set of reservoir releases were determined using the NSGA-II at every control time step. As mentioned previously, MOMPC uses the receding horizon principle, thus, it is required to choose a preferred solution from a Pareto-optimal set at each time step. Therefore, the decision-making procedure is discussed in the next section.

5.2.3. Multi-criteria decision making

Using the MOEA, a set of trade-off solutions can be found in solving an optimization problem with conflicting objectives. Among these solutions, the choice of a preferred solution should be based on qualitative considerations between them. For this task, MCDM technique is a useful tool for evaluating the performance of each alternative solution through multiple criteria. In the decision-making field, several MCDM techniques are available to choose a single preferred solution, for example, weighted-sum developed by Fishburn, ELECTRE proposed by Bernard Roy, TOPSIS developed by Hwang and

Yoon and VIKOR developed by Opricovic [Kumar et al., 2017]. The selection of an MCDM method depends on the decision-maker's preference in term with the ease of use, sensitivity and ability to deal with uncertainty. In this study, the three MCDM methods were used to develop the eight decision rules and their overall performances were discussed. Using the MOMPC, the decision-makers can visually evaluate the performance of each decision rule and can make a choice based on their preferences.

After obtaining the non-dominated solutions from the previous step, feature scaling was used to standardize the all objective costs into a range [0,1] in which 0 means the worst performance and 1 means the best performance for each objective. Suppose, we have m control objectives and s Pareto solutions at each time step, which is normalized as follows:

$$\text{Minimization problem} \qquad J_l^*(u_j) = \frac{\max(J_l(u_j)) - J_l(u_j)}{\max(J_l(u_j)) - \min(J_l(u_j))} \tag{5.4a}$$

$$\text{Maximization problem} \qquad J_l^*(u_j) = \frac{J_l(u_j) - \min(J_l(u_j))}{\max(J_l(u_j)) - \min(J_l(u_j))} \tag{5.4b}$$

$$l = \{1, ..., m\}, \quad j = \{1, ..., s\}$$

After this step, the following decision making methods were applied to select a desired alternative from a Pareto set and it is actually implemented for the next time step $k+1$.

WEIGHTED-SUM METHOD

The weighted-sum method [Hyde et al., 2004; Marler and Arora, 2010] is often used for making decision among a number of alternatives, where an appraisal score is calculated for each alternative solution by multiplying each standardized objective cost by defined weight, followed by the summing up of the weighted scores for all objectives as follows:

$$S_j = \sum_{l=1}^{m} w_l J_l^*(u_j) \tag{5.5a}$$

$$\sum_{l=1}^{m} w_l = 1 \tag{5.5b}$$

Then, an alternative is selected for implementation at time step k that has the highest total score among all alternatives.

$$S = \max(S_j) \tag{5.6}$$

It should be noted that the weighted-sum method applied in Section 5.2.2 is a priori articulation of preference information before optimizing the objective function. In the MOMPC, it is used to select a solution after obtaining a set of Pareto-optimal solutions.

MAXIMIN METHOD

The maximin method [Giuliani and Castelletti, 2016] aims to avoid the worst possible performance of each alternative solution and an alternative is selected as follows:

$$S = \max_j \left(\min_l J_l^*(u_j) \right) \tag{5.7}$$

MAXISUM METHOD

The maxisum method [Giuliani and Castelletti, 2016] focuses on best possible performance of each alternative solution and an alternative is selected as follows:

$$S = \max_j \left(\sum_{l=1}^{m} J_l^*(u_j) \right) \tag{5.8}$$

5.2.4. PERFORMANCES OF THE SYSTEM UNDER ALTERNATIVE OPERATING RULES

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The performance indicators are used to access the possible performance of a reservoir system under alternative operating policies. In this study, reliability of meeting target water levels of reservoirs (or storage volume) was defined based on water level deviation ratio as follows:

$$V_y = \left(1 - \frac{D_y}{\max(D_y)}\right) \times 100, \quad (y = 1, ..., D_r) \tag{5.9}$$

where V_y = reliability of meeting target water levels of reservoirs (%), D_y = water level deviations of reservoirs (m), y = index of the decision rule and D_r = number of decision rules. Similarly, reliability of reducing flood risk at a downstream place is defined as follows:

$$F_y = \left(1 - \frac{E_y}{\max(E_y)}\right) \times 100, \quad (y = 1, ..., D_r) \tag{5.10}$$

where F_y = reliability of meeting flood control objective at a downstream place (%), E_y = exceeding water depth above the danger level (m). For hydropower generation, reliability of meeting target demand is defined as follows [McMahon et al., 2006]:

$$P_y = \left[1 - \left(\frac{Z_y - Z'_y}{Z_y}\right)\right] \times 100, \quad (y = 1, ..., D_r) \tag{5.11}$$

where P_y = reliability of maximizing hydropower generation (%), Z_y = hydropower demand (MWh), Z'_y = generated hydropower(MWh).

5.3. CASE STUDY: A MULTI-RESERVOIR SYSTEM IN THE SITTAUNG RIVER BASIN

The proposed MOMPC method has been tested on real-time operation of a multi-reservoir system in the upper part of the Sittaung river system, Myanmar where a group of reservoirs has been constructed primarily for irrigation, flood protection and hydropower generation (see Figure 5.2). This water system is composed of 11 reservoirs and the readers are referred to Myo Lin et al. [Myo Lin et al., 2018] for the salient features of these reservoirs.

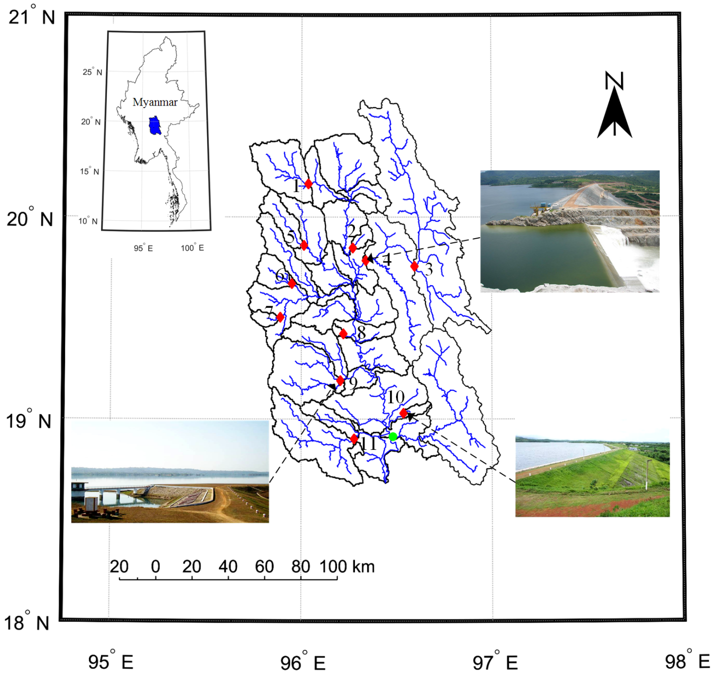


Figure 5.2: Sittaung river basin (Locations of reservoirs are represented with the red diamonds and a flood control point (Taungoo city) is shown with a green dot.).

5.3.1. CONTROL OBJECTIVES

During the dry season, the reservoirs are operated to satisfy two main control objectives, i.e., hydropower and irrigation demand. The reservoirs release water for hydropower generation first and then the water is reused for irrigation through weirs. During the wet season, the reservoirs need to store the water to meet the target storage volumes, while the reservoirs need to release water for hydropower generation. These objectives, however, conflict with each other to maintain the high water levels in the reservoirs for maximizing hydropower production. Moreover, the releases need to be controlled to reduce the downstream flood risk. Therefore, the reservoir operation is particularly challenging in the wet season compared to the dry season. The following control objectives are considered in this study.

1. The first objective (J_1) is to maintain the target water levels of reservoirs (or to store the desired storage volume) for irrigation and hydropower generation in the dry season. Therefore, the deviations of reservoirs' water levels from its reference

levels are minimized by:

$$\min J_1(u) = \sum_{i=1}^{N_r}\sum_{k=1}^{N} w_{h,i}(h_i^k - h_{ref,i}^k)^2 + \sum_{i=1}^{N_r}\sum_{k=1}^{N-1} w_{u,i}(\Delta u_i^k)^2 \tag{5.12a}$$

$$\Delta u_i^k = u_i^k - u_i^{k-1} \tag{5.12b}$$

where h_i = water level at reservoir i (m), $h_{ref,i}$ = reference water level of reservoir i (m), u_i = controlled outflow at reservoir i (m^3/s), Δu_i = change of control flow at reservoir i (m^3/s), $w_{h,i}$= weighting factor for water level deviation of reservoir i, $\Delta w_{u,i}$= weighting factor for the change of conduit flow at reservoir i, and N_r = number of reservoirs (11 Nos.).The maximum allowed value estimate (MAVE) [van Overloop, 2006b] was used to define the penalties on the change of water level and the conduit outflow. In this study, maximum allowed water level relative to reference level and maximum allowed discharge relative to the conduit capacity were used as MAVE of that variable. The penalties were defined to the reciprocal of the square of the MAVE of that variable.

2. The second objective (J_2) is to reduce the flood risk at Taungoo city. A soft constraint [van Overloop, 2006b] is implemented to minimize the water level deviations from the safety water level at Taungoo city, which is defined as:

$$\min J_2(u) = \sum_{k=1}^{N} w_{h,p}(h_p^k - u_*^k)^2 + \sum_{k=1}^{N} w_{u_*}(u_*^k)^2 \tag{5.13a}$$

$$u_*^k = \begin{cases} h_p^k & \text{if } h_p^k \le h_{p,sl} \\ h_{p,sl} & \text{if } h_p^k > h_{p,sl} \end{cases} \tag{5.13b}$$

where h_p = water level at river reach p (m), u_* = soft constraint [van Overloop, 2006b] on water level at river reach p (m) and $h_{p,sl}$ = safety water level at river reach p (m).

3. The last objective (J_3) is to maximize electric energy production of reservoirs which is defined as [Ref]:

$$\max J_3(u) = \sum_{i=1}^{N_r}\sum_{k=1}^{N} \eta_i g \gamma u_i^k (h_i^k - h_{tw,i}^k).10^{-6} \tag{5.14}$$

where $h_{tw,i}$ = tail water level of reservoir i (m), η_i = coefficient of turbine efficiency ranging from 0 to 1 (0.6), g = acceleration due to gravity (9.81 m^2/s), γ = density of water (1000 kg/m^3), and N_r = 3.

This optimization problem can be written as:

$$\min J(u) = \{J_1(u), J_2(u), -J_3(u)\} \tag{5.15a}$$

subject to

$$x^{k+1} = A_x^k x^k + B_u^k u^k + B_d^k d^k \tag{5.15b}$$

$$u_{i,\min}^k \leq u_i^k \leq u_{i,\max}^k, \quad \forall k \tag{5.15c}$$

$$h_{i,\min}^k \leq h_i^k \leq h_{i,\max}^k, \quad \forall k \tag{5.15d}$$

5.3.2. MODEL DESCRIPTION

In this study, we employed the same rainfall runoff and internal model used by Myo Lin et al. [2018] to implement the MOMPC framework in the Sittaung river basin. The Sittaung catchment was divided into 34 sub-catchments and their outflow was estimated using the Sacramento rainfall runoff models. As described in Section 5.2.1, the river system was divided into 82 reaches, and a one-dimensional de Saint-Venant equations based internal model was used to estimate the water levels and flow of the system. The Sittaung reservoir system was also modelled by using SOBEK developed by Deltares [Deltares, 2016] to represent as a real water system that was used to update the water levels and flow of the simplified model.

5

5.3.3. SIMULATION SETTINGS

Model simulation was conducted for 10 days using 30 minutes discrete time steps. The NSGA-II was applied to optimize the cost function (Equation (5.15a)) over a two days prediction horizon which proved long enough to capture the dynamics of the water system [Myo Lin et al., 2018]. The parameters of NSGA-II are shown in Table 5.1.

Table 5.1: Parameters of NSGA-II.

NSGA-II parameters	**Setting value**
Population size	200
Maximum number of generations in each run	1200
Crossover rate	0.80
Mutation rate	0.35
Stopping criteria	1. The average change in the spread of the Pareto front over generation (=100) is less than or equal to function tolerance (10^{-4}). 2. The maximum number of generations is reached.

As the receding horizon control was applied, each model simulation used a decision rule (DR), shown in Table 2, to select a release decision at every time step for the whole simulation horizon. Three commonly used MCDM methods were applied and compared their performances. For weighted sum method, the weights were defined to explore the conflicts between management objectives. The highest weight for each objective was used in DR 1, DR 2 and DR 3 to find out the best possible performance of each objective without considering all other objectives. The different weight combination were also used to analyze the trade-off and priority of each objective. To support the decision makers, model simulation was performed eight times to assess the overall performance for the different decision criteria. For the weighted-sum method, a weight matrix is defined as:

$$w = \begin{bmatrix} w_1 \\ w_2 \\ w_3 \end{bmatrix} \tag{5.16}$$

Table 5.2: Decision rules used in this study.

Decision rule	Method	w
DR 1	weighted-sum	[1,0,0]
DR 2	weighted-sum	[0,1,0]
DR 3	weighted-sum	[0,0,1]
DR 4	weighted-sum	[0.6,0.2,0.2]
DR 5	weighted-sum	[0.2,0.6,0.2]
DR 6	weighted-sum	[0.2,0.2,0.6]
DR 7	maximin	-
DR 8	maxisum	-

5.4. Results

The proposed MOMPC scheme was applied to the Sittaung reservoir system for real-time operation of a multi-reservoir system involving the three control objectives. Model simulation was conducted for 10 days (simulation horizon) using 30 min discrete time steps. For the Sittaung catchment, the travel time of the water flow from its origin to the outlet takes 41 hr for the average flow condition. In this study, as two days prediction horizon was used, it was able to capture the dynamics of water system for the MOMPC formulation. Model was run on 2.5 GHz Intel Core i5 processor 8G RAM computer and the average computation time was 100 sec in each time step. This efficiency allows us to update the reservoir operation policy in real-time. The inflows into the reservoirs are shown in Appendix (A.6).

5.4.1. Pareto Fronts and Trade-offs

Multi-objective optimization with NSGA-II generates a set of non-dominated solutions in a single run which is beneficial for the decision makers to make a release decision based on their preferences. In every simulation time step, a Pareto optimal solution set was obtained and a solution was selected for implementation at the current time step.

According to the results, the different competitions occurred among the control objectives in a simulation horizon. Figure 5.3(a-d) shows an example of the obtained Pareto front for a particular time step and illustrates the trade-offs using the eight different decision rules. Figure 5.3(a) shows that a clear conflict between minimization of reservoir storage deviation (J_1) and the prevention of flooding (J_2). The best performance in terms of J_1 is obtained by DR 1, while the lowest performance can be achieved in terms of J_2. A weak conflict exists between J_1 and J_3 (Figure 5.3(b)) because minimization of storage deviation needs to release the water, which is available for hydropower production. Results also show a clear trade-off between J_2 and J_3 (Figure 3(c)), where DR 3 can achieve the highest performance in terms of J_3, while the lowest performance is obtained in terms of J_2. Figure 5.3(d) reports the projection of non-dominated solutions in the three dimensional plot using the different colours. The green, blue and red colours represent the performance of each solution in terms of J_1, J_2 and J_3, respectively. The circle's size further indicate the better solution in terms of the three objectives. A solution becomes better in terms of J_1 (green) and J_2 (blue); the colour is shown in cyan. A solution becomes better in terms of J_1 (green) and J_3 (red); the colour is shown in yellow. A solution becomes better in terms of J_2 (blue) and J_3 (red); the colour is shown in magenta. The highest performance in terms of J_2 is shown in the colour blue under DR 2 (see Figure 5.3(d)). DR 3 is shown with the yellow colour in Figure 5.3(d) which has the high performance in terms of J_3 and J_1 as well. The large circles with light colour (e.g. DR 4, DR 7 and DR 8 in Figure 5.3(d)) represent that the solutions become better in terms of all objectives.

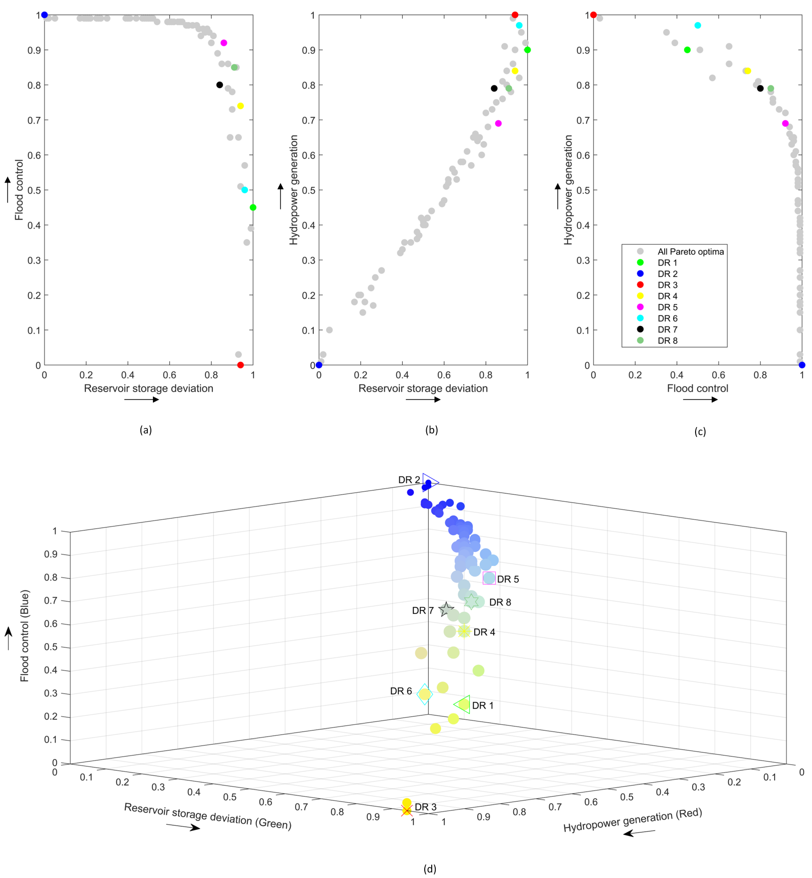


Figure 5.3: (a-c) Two dimensional Pareto front and selected solutions using different decision criteria, (d) Three dimensional Pareto front and selected solutions using different decision criteria (The objective costs are normalized and the black arrows indicate the direction of increasing preference.).

Figure 5.4(a-d) shows the obtained Pareto front for another time step. There is a weak conflict between J_1 and J_2 (Figure 5.4(a)), however, a clear conflict exists between J_1 and J_3 (Figure 5.4(b)). This means that the maximization of hydropower generation causes large deviations in the reservoir storages. Figure 4(c) shows that DR 2 has the negative impact in the hydropower generation. Figure 5.4(d) clearly represents the performance of each decision rule in terms of the three objectives. DR 1 has the high performance in terms of J_1 and J_2, while a low performance is obtained in terms of J_3 (Figure 5.4(d)). DR 2 has the worst performance in terms of J_3 and DR 3 has the worst performance in terms of J_1. DR 5, 7 and 8 have the better performances in terms of the three objectives compared to all other solutions.

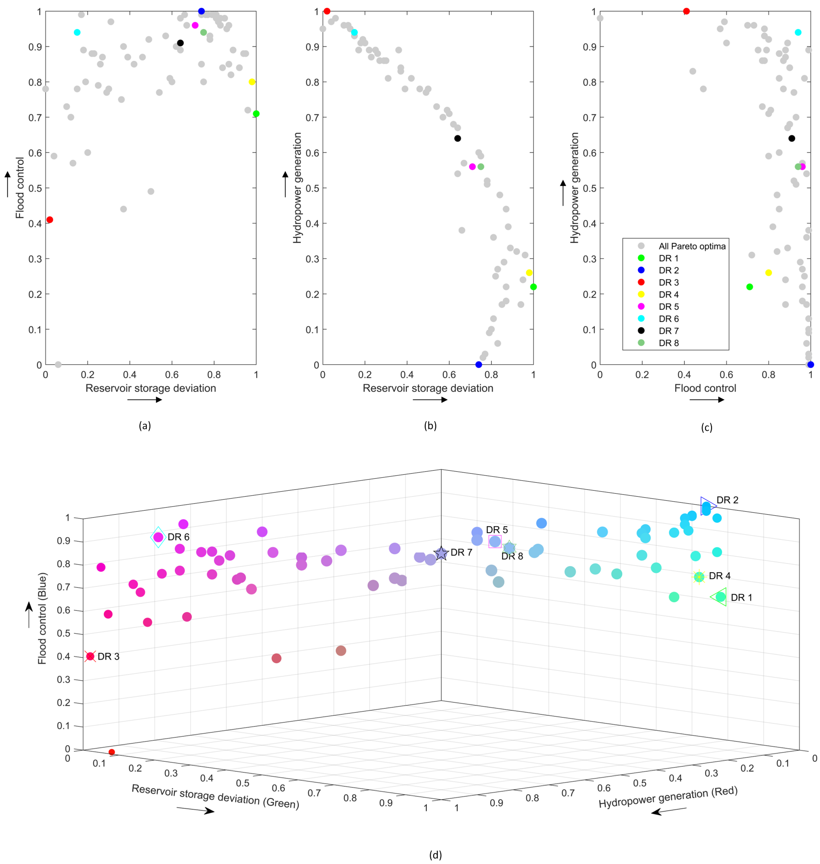


Figure 5.4: (a-c) Two dimensional Pareto front and selected solutions using different decision criteria, (d) Three dimensional Pareto front and selected solutions using different decision criteria (The objective costs are normalized and the black arrows indicate the direction of increasing preference.).

5.4.2. PERFORMANCE OF THE SYSTEM

An example of water level control at the reservoirs is shown in Figure 5.5 a–d. DR-1 focuses to control the water levels of reservoir to meet the desired storage capacities. For this operational goal, MOMPC manipulates the outflows of reservoirs to keep the reservoir water levels as close to the reference water levels as possible. In case, inflow exceeds the maximum conduit capacity, a large deviation occurs between the reservoir water level and target water level (Figure 5.5 d). As the eight decision rules are applied in this study, the water levels of reservoirs under the different operating rules are shown in the Appendix (A.7).

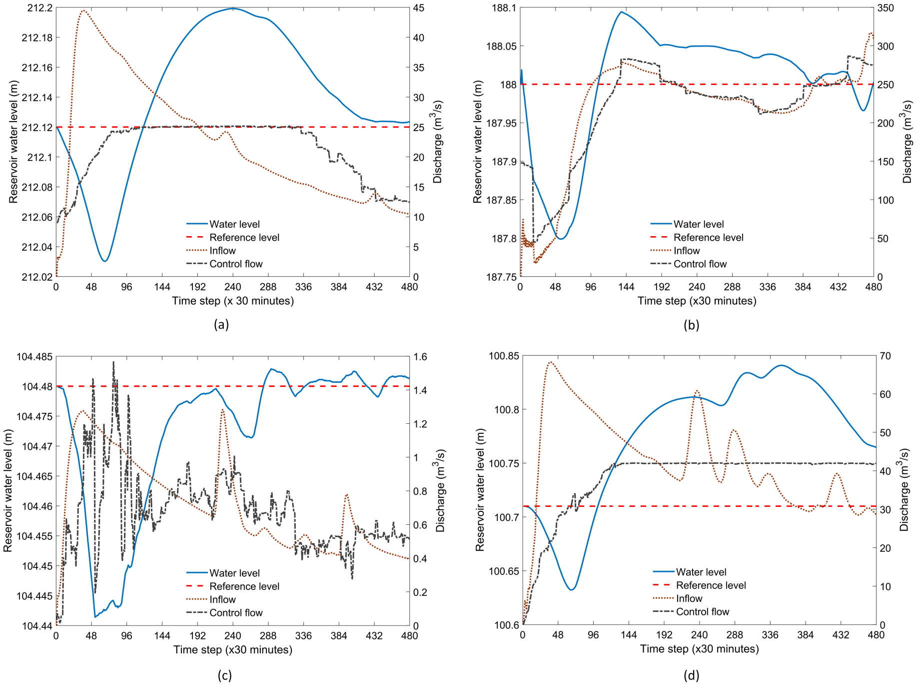


Figure 5.5: (**a–d**) Inflows, outflows and water levels of reservoirs 1 (**a**), 4 (**b**), 8 (**c**) and 9 (**d**) under DR-1.

In Figure 5.6, the water levels at a downstream control point exceeded above the danger level using the different decision rules except DR-2. However, the exceeding water depth and total exceeding time above the danger level vary under each decision rule. Using DR-2, the second objective was focused and reservoir releases were restricted to meet flood control gold. The maximum exceeding water depth can be achieved by using DR-3 and 6 (0.5 m) and the exceeding time above the danger level can last around 7 days compared to the results of the other decision rules.

Figure 5.7a–c shows the total generated hydropower under DR-1, 2 and 3 respectively. DR-2 generates less energy compared to the other rules that it mainly focuses to meet the flood control objective (Figure 5.7 b). DR-3 aims to maximize the energy production that can make the other objective worse off (see Figure 5.6) and Appendix A.7.

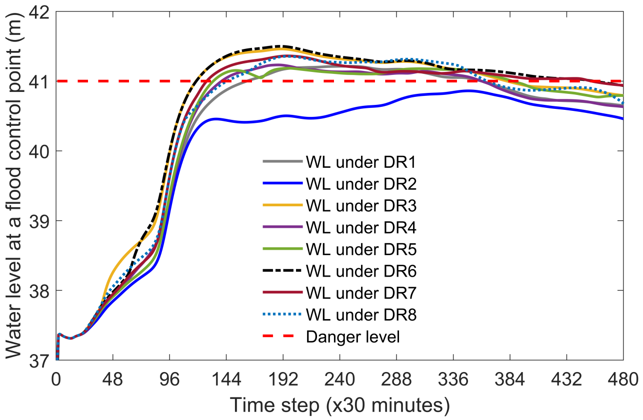


Figure 5.6: Water level at the downstream control point.

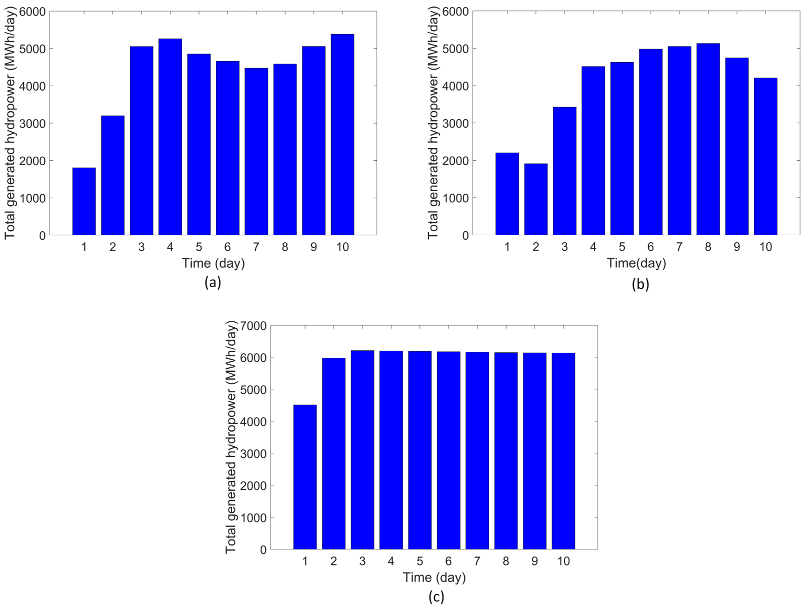


Figure 5.7: (**a–c**)Total generated hydropower under DR 1 (**a**), 2 (**b**) and 3 (**c**).

5.4.3. OVERALL PERFORMANCE

The parallel line visualization in Figure 5.8 helps the decision makers to clarify the differences in the eight decision rules. The overall performance of each decision rule is presented as a line crossing the vertical axes at the objective values of their corresponding performance. The objective values are shown with their minimum and maximum values and the axes are oriented so that the direction of preference is all downward. Compared to other decision rules, DR 1 has the lowest deviation to the target water levels in the reservoirs. DR 2 achieves the highest performance in flood control, while it has the lowest hydropower production. DR 2 has the highest performance in hydropower production, but has the lowest performance in water level deviation and flood control. DR 4, 5, and 6 clearly show that a high performance could be achieved by applying more weight to a particular objective. DR 7 and 8 show a similar performance in water level deviation and flood control, however, they have a small difference in hydropower production. This parallel line plot shows that DR 7 achieves a well-balanced overall good performance in all objectives.

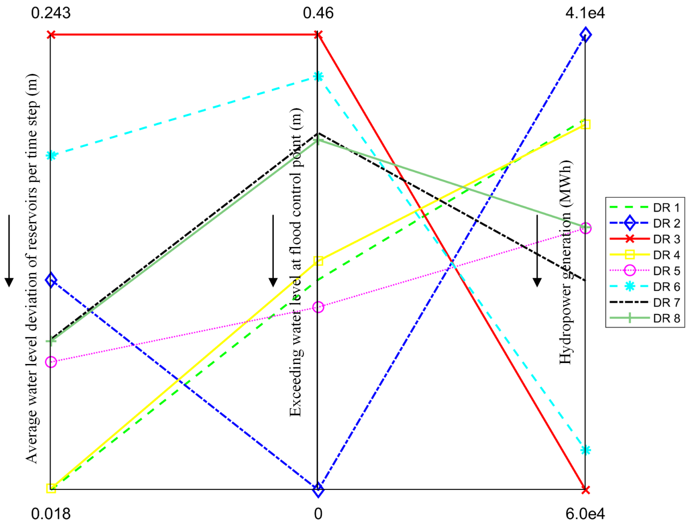


Figure 5.8: Parallel line plot for the eight decision rules (Each line represents the overall performance of the three objectives with respect to a particular decision rule and the black arrows indicate the direction of good preference.).

5.4.4. Comparison of Results

Table 5.3 compares the results of the eight decision rules. Among them, DR-1, 2 and 4 have the overall performance greater than 70% compared to other decision rules. The results show that the improvement of storage reliability can certainly increase the flood risk, while a deficit occurs in hydropower production. On the other hand, flood risk could be eliminated by allowing deficits in storage volume and power generation. Similarly, reliability of meeting hydropower demand can be improved while degrading the performances of other objectives. The results provide a range of alternatives and help to realize the conflicting behavior in a reservoir system operation.

Table 5.3: Performances of the system under alternative operating rules.

Decision Rule (Weight)	Indicator			Overall Performance (Average)
	Reliability of Meeting Storage Capacity V (%)	**Reliability of Meeting Flood Control E (%)**	**Reliability of Maximizing Hydropower Generation P (%)**	
DR-1 (1,0,0)	93	54	74	74
DR-2 (0,1,0)	50	100	68	73
DR-3 (0,0,1)	0	0	100	33
DR-4 (0.6.0.2.0.2)	92	50	74	72
DR-5 (0.2,0.6.0.2)	67	60	82	69
DR-6 (0.2,0.2,0.6)	25	9	97	44
DR-7	62	22	85	56
DR-8	62	23	82	56

5

5.5. Discussion

In this section, we discuss the use of NSGA-II in MPC formulation, the selection of MCDM methods and the limitations of the proposed method.

5.5.1. The use of GA in MPC formulation

The main advantages of the MOMPC compared to the classical MPC are the ability to find the real-time Pareto optimal solutions and to make the preferred decision using one of the available MCDM methods. This creates more flexibility to solve multi-objective control problems. As mentioned in Section 5.1, other advantages of this approach are that NSGA-II can deal with non-linear, non-differentiable and non-continuous optimization problems.

5.5.2. Selection of a decision making method

Generally, a multi-objective optimization problem may have a number of alternative solutions. For making a decision, MCDM supports the decision-makers to choose the best alternative from a set of possible alternatives. In this study, we used the three MCDM methods to test our MOMPC approach. For the weighted-sum method, the weights are defined to reflect the relative importance of each objective. It is difficult to identify the relative weights when many stakeholders involve in the decision-making process. In this study, we did not emphasize to find the best weight combinations, but the different weight combinations were used to identify the trade-offs among the conflicting objectives. maximin and maxisum decision rules are also applicable to make a decision, however, the decision-maker's preference lead for the selection of a MCDM method. For this purpose, the other decision-making methods, for example, TOPSIS, VIKOR and ELECTRE, could be applied in the MOMPC approach.

5

5.5.3. Limitations of the method

The main drawback of MOMPC method is the computational efficiency compared to the classical MPC. The computational time required to find a solution was 100 sec per optimization iteration using NSGA-II with 2.5 GHz Intel Core i5 processor 8G RAM computer compared to 6 sec for the case using the interior point method with the same computer. Although the computational time of MOMPC is greater than the classical MPC, it is still applicable to use for real-time reservoir operation. However, further investigation is needed for more complex applications. In this study, we emphasize to solve a multi-objective control problem in a multi-reservoir system using the deterministic inflow forecasts. This can deteriorate the MPC performance in real world implementation. Nevertheless, note that this issue is beyond the scope of the current study. there are also specific methods to deal with uncertainty such as stochastic MPC [Maestre et al., 2013; Tian et al., 2019], which could be applied to mitigate this issue.

5.6. Conclusions

A methodology combining MPC with GA was proposed for real-time operation of a multi-reservoir system. It has been demonstrated through the application to the Sittaung river basin that this approach is able to find the compromise solution for a multi-objective control problem. Another advantage is that the decision-makers can visually evaluate the trade-off solutions and the effects of different decision rules during model simulation. Moreover, this study presented the use of the weighted-sum, the maximin and the maxisum methods for the decision-making process. In this way, a parallel line plot can be built to support the decision-makers in the assessment of the overall system performance using the different MCDM methods. Thus, the decision-maker's preference becomes explicit in the selection of a MCDM method. To illustrate our approach, three operational objectives are considered in the Sittaung reservoir system but many objectives may involve in other cases. Therefore, further testing and verification of the proposed methodology in other problems is still necessary. In addition, future research could use the ensemble forecast in MOMPC formulation [Raso, 2013; Tian et al., 2017] to address the inflow uncertainty.

6

Improving reservoir operation in the Sittaung River Basin

This chapter discusses the potential of improving reservoir operation in the Sittaung river basin.

6.1. BACKGROUND

The Sittaung river is a main river of Myanmar and lies in the country's central zone. It runs from the north to south direction with a length of 420 km and ends up into the Gulf of Martaban. The catchment area is about 33665 sq-km and estimated annual surface runoff is about 45 km3. It has 23 major tributaries which flow into the sittaung river from the east and west. About 6 million people reside in this area and agricultural sector plays a major role in regional development and poverty reduction. Due to climate and topographic conditions, average annual rainfall amounts vary from low in the north (< 1000 mm) to high in the south (>3000 mm). About 80 % of total rainfall receive during monsoon season starting from mid-May to October. The remaining 6 to 7 months are the dry period with little rainfall. The common water-related problems occurred in the Sittaung river basin are droughts at the upper part, floods at the middle and lower parts, and river bank erosion and sea water intrusion at the lower part of the basin. Generally, rice, a main crop in Myanmar, is grown in the monsoon season and cannot be grown in the dry season without irrigation. In 1964, the Myanmar government developed a master plan for multipurpose utilization of water resources in the Sittaung river basin, with technical assistance from the United Nations' experts. It is a long-term development project including the construction of new reservoirs for irrigation, hydropower generation, drinking water supply and flood control, and construction of drainage channels, new sluice gates and embankments for flood management at the middle and lower part of the river basin. At present, most of the projects involved in a master plan (1964) have been implemented and they are now serving to meet various water management objectives.

As the results, the irrigable area is increased about 73000 hectares and the installed capacity of hydropower reaches up to 500 MW by the construction of the new reservoirs and weirs. In addition, a total land area of 36000 hectares is protected from flood by the construction and upgrading of embankments, drainage channels and sluice gates. Although regional development has been achieved by the implementation of water management projects in the recent years, several challenges still remain and need to be addressed for further development, such as the developing overall policies, legislation and institutional structure, improving monitoring network and data availability (e.g., rainfall, runoff, water level), adaptation of climate change, maximizing benefits from existing water-related structures, and environmental conservation. As more than 20 reservoirs have been constructed in the Sittaung river basin for irrigation, hydropower generation and flood control, it is required to upgrade the current operation and management system more efficiently for maximizing the benefits from the existing reservoirs and minimizing social and environmental impact. This non-structural measure can improve the services of reservoirs with little incremental cost. This means that water for irrigation, hydropower generation can be used more efficiently and river flow can be controlled more effectively to reduce the flood damages at the downstream area. The improvement on reservoir operation must be capable of functioning effectively under conditions of changing supplies, management objectives and demands. To improve reservoir operation, this study focuses on the development of a real-time decision support system using real-time data, forecasting, optimization and simulation. The improvements such as sediment control and structural safety are other aspects of reservoir operation and management.

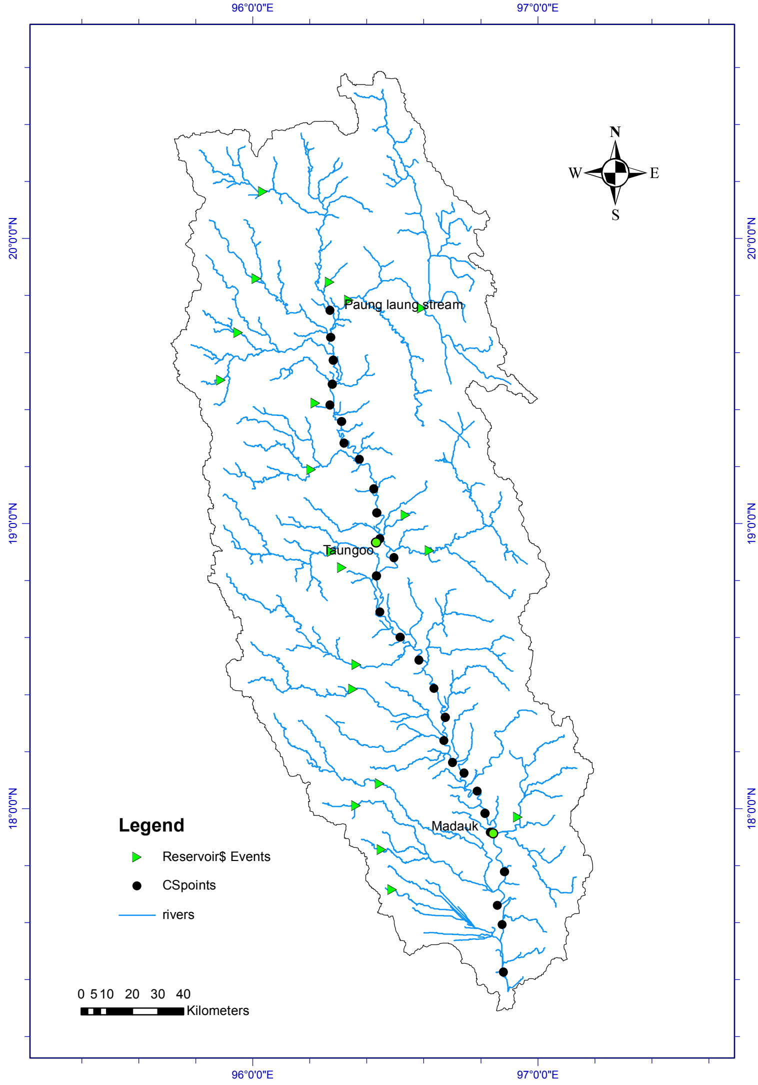


Figure 6.1: Location map of reservoirs.

6.2. CURRENT RESERVOIR OPERATION IN THE SITTAUNG RIVER BASIN

In the Sittaung river basin, most reservoirs are operated by the Irrigation and Water Utilization Management Department IWUMD) which is a state-owned institution under the umbrella of the Ministry of Agriculture, livestock and Irrigation. Among 20 reservoirs, there is a reservoir under a private company for hydropower production. A joint operation is carried out between IWUMD and a department under the Ministry of Electricity and Energy if a reservoir is used for hydropower generation and as well as for irrigation. During the flood season, reservoirs are also used to retain the incoming flows to reduce the downstream flow rates for flood protection. Figure 6.1 shows the seasonal water level fluctuations of a reservoir in which the reservoir stores the water during the rainy season (mid-May to October) and supplies the water in the dry season for irrigation and hydropower production. During the wet season, there are the three operational objectives, hydropower generation, flood control and water level control at a reservoir to store the water for later use in the dry season. In the dry season, there is less or without rainfall and the operational objective is to meet the demand for irrigation and hydropower generation.

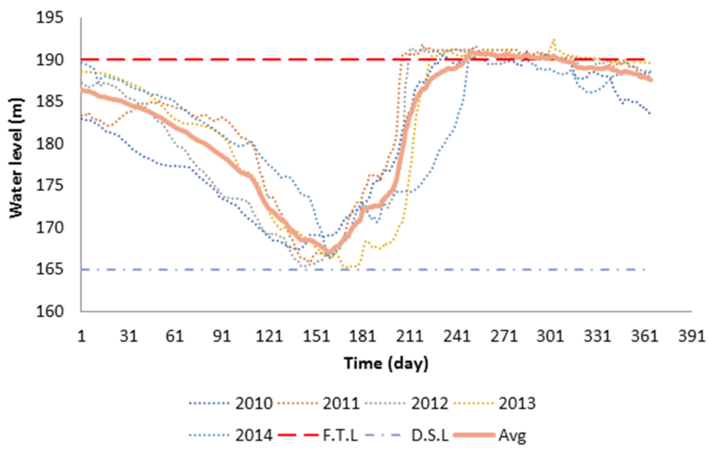


Figure 6.2: Seasonal water level fluctuation of lower Paung Laung reservoir.

In Myanmar, reservoir operation is mainly based on inflows and storage levels of a reservoir. Reservoir release is decided by an operator based on inflow, demand and the current water level of a reservoir. There is no measurement on incoming flows into the reservoir and only the daily rainfall is measured at the reservoir. For the inflow estimation, reservoir operator uses the average rainfall record to estimate the inflows to a reservoir. Therefore, inflow estimation is highly uncertain and water shortage or flood often occurs due to overestimation or underestimation of inflows. In addition, there is the potential conflict in multi-purpose operation, for example, maximizing hydropower production and reducing the flood peak at the downstream area. A reservoir typically has two outlet structures, a spillway and a conduit. Most of the spillways are free overflow spillways with no gates and they are designed to withstand for return-period of 1,000-year flood. The conduits have been designed to meet the required discharge for hydropower production or irrigation water supply. Therefore, there is a constraint for the flood operation to create a storage space in advance before coming the extreme flood if the capacity of a conduit is inadequate to release the required water volume within a forecast horizon. To deal with this constraint, storage spaces for flood control need to be defined in all reservoirs and it should be kept empty during the rainy season to store incoming flows for minimizing flood risk at the downstream areas. Moreover, it is required to improve the current reservoir operation for meting the growing demands and for adapting the changing climate in the future.

6.3. IMPROVING RESERVOIR OPERATION IN THE SITTAUNG RIVER BASIN

As the technology has been developed, currently, several methods are available for improving the current reservoir operation in the Sittaung river basin. An extensive review of the available methods can be found in Chapter 2. These methods may be categorized as simulation, optimization and the combined simulation-optimization approach. In the Sittaung river basin, floods often occur at the middle part and the lower part of the basin. The releases of the upstream reservoirs contribute the flow changes at the downstream areas. A simulation model is required to predict the water levels and flows of the system under alternative operating policies. Several reservoirs are used for multiple purposes and multi-objective optimization is also required to find the compromised solution between the conflicting objectives. Therefore, a decision-support system for reservoir operation in the Sittaung river basin should be based on a combined simulation-optimization approach.

6

6.3.1. DECISION-SUPPORT SYSTEM USING MODEL PREDICTIVE CONTROL

Chapter 4 presents the potential of reducing flood risk in the Sittaung river basin using a combined simulation-optimization approach called Model predictive Control. The comparison between the current operation and MPC operation was done. The result shows that the flood peak at the control point is decreased to 0.5 m under MPC operation. In this study, reservoir releases were optimized to mitigate the flood risk at the downstream area and the other objectives, water level control in the reservoirs and hydropower generation were considered as the constraints. As MPC controller uses real-time information, it is required to upgrade the current monitoring system for implementation of MPC in the Sittaung river basin. In addition, the storage spaces for flood prevention need to be specified in all reservoirs to overcome the constraints on the conduit capacities.

6.3.2. DECISION-SUPPORT SYSTEM USING MULTI-OBJECTIVE MODEL PREDICTIVE CONTROL

To solve the conflict between multiple objective, Chapter 5 presents real-time operation of the Sittaung reservoir system using the proposed multi-objective MPC. This method is able to find the Pareto optimal solutions for a multi-objective optimization problem and is able to choose a preferred solution under the defined decision criteria. The results show that it supports the decision-makers for resolving conflict over reservoir operation.

6.4. CONCLUSIONS

As the analysis, it is impossible to completely eliminate the flood risk in the Sittaung river basin because of the limitations on the storage capacities of reservoirs and capacity of conduits. It is suggested to consider the new structural measures such as construction of flood retention reservoirs at the middle and lower part of the basin for preventing the floods near the Taungoo and the Maduk areas. The improvement on the current reservoir operation should be done in step by step. Firstly, it is required to upgrade the current monitoring system for providing real-time information such as rainfall, water level and flow. Secondly, the proper rainfall-runoff models should be developed to estimate the outflows of the sub-catchments. Then, a combined simulation-optimization approach such as MPC could be implemented to improve the current reservoir operation in the Sittaung river basin.

7

Conclusions and Recommendations for Future Research

There are many challenges to develop a decision-support system for real-time operation of a reservoir system. Some of them have been addressed in this study and some of them still need to be overcome in the future study.

7.1. Application of Model Predictive Control for Real-Time Reservoir Operation

Reservoirs play a significant role in water resources management by providing irrigation, hydropower, flood control and navigation etc. Reservoir operations aim to fulfill the desired objectives by releasing the required quantity of water to right place at right time. In the context of reservoir operation, seasonal variation of inflow, water use and drought are considered as the long-term operation using weekly, monthly or yearly time step. Operation of flood or emergency situation is usually considered as short-term operation using hourly or daily time step. Various methods are available for long-term or short-term reservoir operation analysis. Using MPC, this thesis evaluates the potential for improving the performance of a reservoir system in real-time and focuses on multi-objective optimization.

7.2. Conclusions

The sub-question (a) is answered in Chapter 4. A typical quadratic formulation of MPC controller was developed for a large-scale reservoir system in which a simplified internal model was used to predict the current and future states of the system. A real-world case study was conducted for flood mitigation at a downstream area by controlling the water levels of reservoirs and a river reach. The results show a clear improvement in flood risk reduction using MPC compared to the current operation of existing reservoirs.

Chapter 5 addresses sub-question (b) by developing MOMPC. In comparison to classical MPC, this approach offers flexibility in making a preferred decision through the visualization of multiple trade-off solutions in real-time.

7

To answer the main research question in Chapter 1, MPC is a promising method for improving the operation of controlled reservoir systems when they perform poorly using conventional control methods. The advantages are its ability to deal with system dynamics, multi-objective and constraints. In the following sections, we discuss the use of MPC in reservoir operations.

7.2.1. Modelling of reservoir systems

A process or an internal model is an element of MPC which is used to predict the current and future system states. In this thesis, a linear time-varying state space model based on Saint-Venant's equations was used as a process model. A large grid size and a large time step discretization scheme [Tian et al., 2015] was adopted to develop a system model. This model is able to capture the dynamics of a reservoir system and the computational efficiency is acceptable to control a large-scale water system.

7.2.2. Multi-objective optimization

In MPC, the optimal reservoir releases are determined by optimizing an objective function. Various optimization methods can be applied in MPC formulation to find the optimal control actions. However, it is required to use a suitable optimization method to solve a real-time control problem. An optimization method, such as dynamic programming takes long time to find an optimal solution for a large-scale water system. In general, LP or QP based optimization method requires less computational time to find the solutions compared to other optimization methods.

In a standard MPC, a weighted-sum or a constraint method are usually used for solving multi-objective control problems. However, these methods are limited to evaluate all possible Pareto optimal solutions in a single run. Evolution based algorithm, such as MOEA is a powerful tool to search a Pareto optimal set in a single run. In Chapter 5, a standard MPC was extended to MOMPC by incorporating with MOEA. This approach is able to search all Pareto optimal solutions at every control step and provides a flexibility for selecting a desired solution in a decision-making process. Moreover, how to choose a preferred solution from a Pareto optimal set using a MCDM was also presented. Thus, MOMPC is applicable for real-time control of a single or multi-reservoir system with multiple objectives. This approach can also be used for any other systems after reformulating a process model and the objective functions.

7.2.3. REAL WORLD IMPLEMENTATION

In Chapter 2, MPC was used to control the water levels of reservoirs and a river reach subject to capacities of conduits and released discharge for hydropower and irrigation. This MPC formulation was based on a linear state space model and a quadratic cost function with linear constraints. This type of MPC formulation is easy to tune and implement in real world practically. The computation time takes less than 20 sec for a simulation time step that makes it reasonable to use for a real-time control. However, it is required to address inflow uncertainty and the conflicting interest between multiple objectives. An MOMPC approach presented in Chapter 5 overcomes an issue for multi-objective optimization. This approach is able find an optimal solution in real time and more flexible than a standard MPC. A drawback of this approach is the computational efficiency. Model was run on 2.5 GHz Intel Core i5 processor 8G RAM computer and the average computation time was 100 sec in each time step. Therefore, it is 5 times larger than the standard MPC running with same computer. Thus, it is required to investigate the computational efficiency when a reservoir system composed of more than more than eleven reservoirs. In addition, it is required to address uncertainty such as inflows to the reservoirs in the MPC formulation. Therefore, the proposed MOMPC method need to be incorporated with the ensemble stream flow forecast to deal with inflow uncertainty for practical implementation.

In this research, a reservoir system was also modelled by using SOBEK hydrodynamic software and it was considered as an actual water system. Instead of using the actual measurements, SOBEK model was used to update the water levels of MPC controller (feedback action). For real world implementation, the actual measurements need to be used for updating the system states of MPC controller. As MPC requires real-time information, a real-time monitoring network for water flows and water level measurements is required to control a large-scale water system.

Some regions in the world, especially for developing countries like Myanmar, may not fulfill all requirements to implement a fully automatic control system, for example, lack of monitoring facilities. For this case, a modified control configuration, the combination of a centralized predictive control and human operators in the control loop [Maestre et al., 2014], should be implemented. In this approach, human operators receive the control actions from a centralized MPC controller through mobile phones and implement it into the system. They send back the measurements of the system states to control center to get the next instruction. In this way, a semi-automatic control system can be implemented in the developing regions.

In reality, reservoirs are individually operated by local water authorities of a river basin. A centralized configuration is required when a management objective is influenced by releases from two or more reservoirs. The coordination and cooperation between the different authorities are required in order to satisfy not only local management goals but also common management goals, for example, flood control at the downstream river reaches. Sometimes, a centralized control setup may have a low performance due to lack of coordination between sub-systems. A hierarchical distributed MPC [Negenborn and Maestre, 2014; Zafra-Cabeza et al., 2011] has the potential for addressing the conflicts between local objectives and regional objectives. This approach involves two levels MPC controllers, a higher level and a lower level. At the lower level, each local controller of a reservoir manipulates local control goals and exchanges information to other reservoir controllers. Meanwhile, the upper level receives the overall information and sends local control goal to each reservoir when a flood or a drought are expected at the downstream river reaches [Negenborn and Maestre, 2014]. In this way, a large-sale problem is reduced to smaller sub-problems which may be easier to solve and may take less computational time. In the Sittaung river basin, reservoirs are operated by the different agencies,the government agencies and the private companies. There is a weak coordination between them and the distributed MPC approach may provide a better performance than the standard MPC.

7.3. Recommendations for Future research

This research presents operation of a reservoir system and focuses on a real-time control and the multi-objective optimization. Real world case studies presented in Chapter 4 and 5 show that applicability of the proposed method to control multi-reservoir systems. There is no a unique algorithm to operate all reservoir systems because every reservoir system has its own characteristics. The propose algorithms need to be modified in the internal model and the objective functions when the different types of structures and objectives are used in the other reservoir systems. Besides that, the following sections discuss the recommendations for future research to extend the proposed methods for real-world implementation.

7.3.1. Inflow uncertainty

In this research, MPC formulation is based on a deterministic approach in which future states of the system is developed without involving a stochastic nature. A prediction of inflow to reservoir is affected by hydrological uncertainties. It is a main source of uncertainty for a reservoir system analysis. To deal with this uncertainty, recent studies adopted ensemble forecast (e.g. rainfall or streamflow) to generated the disturbance tree or scenarios and incorporated these scenarios in an internal model for finding efficient solutions at every control time step [Ficchì et al., 2016; Raso et al., 2014; Tian et al., 2017]. These studies recommend that the proposed methods are able to handle hydrological uncertainties and applicable to use for real-time control of water systems. However, the computation time is increased by using these methods compared to a deterministic approach. In addition, an efficient multi-objective configuration is out of the scope of these studies. Therefore, a direction of future research is to extend MOMPC method considering uncertainties of disturbances and investigates the computational efficiency for real-time control of large-scale reservoir systems.

7.3.2. DISTRIBUTED APPROACH FOR COMPLEX RESERVOIR SYSTEMS

A large-scale reservoir system is composed of several reservoirs operated by different water authorities. Each authority has their own management goals and, on the other hand, each action taken by different water authorities may have the negative impacts such as flood, drought and environmental issue at the downstream river reaches. Thus, multi-reservoir operations are required to compromise between conflicting objectives in order to satisfy all management goals. However, a centralized control configuration sometimes fails to achieve the desired performance due to complexity of system dynamics, lack of coordination between sub-systems and low computational efficiency. For this case, an alternative way is using a distributed model predictive control approach in which each sub-system has its own MPC controller. This is a direction of a future research to extend the proposed MOMPC methods for controlling more complex reservoir systems.

A

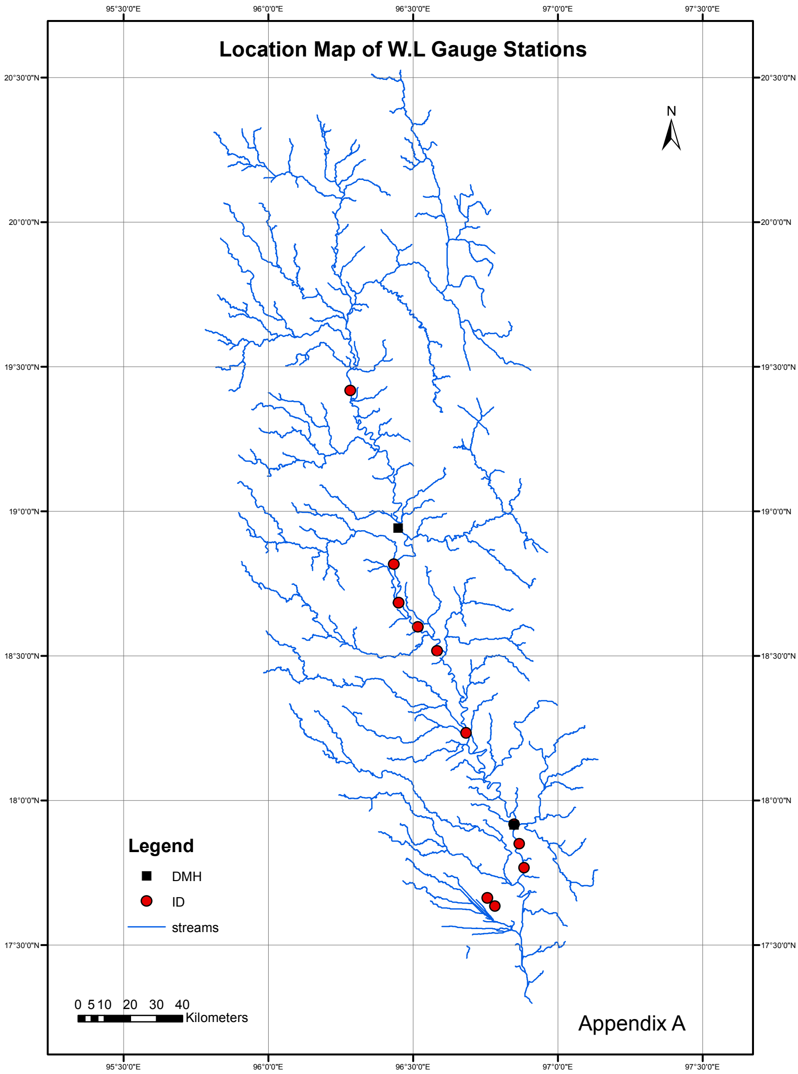
APPENDIX

A.1. LIST OF IWUMD WATER LEVEL GAUGE STATIONS ALONG THE SITTAUNG RIVER.

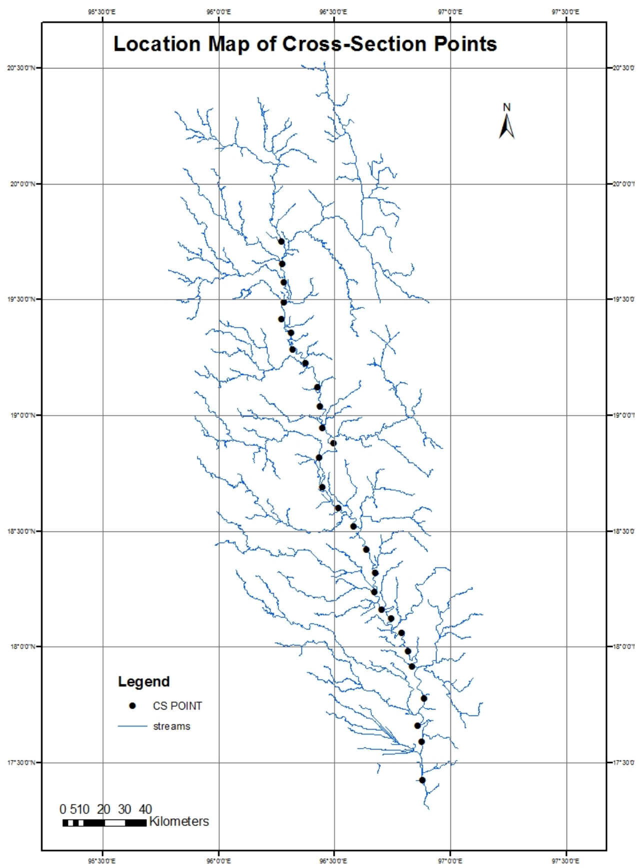
Sr. no.	Station Name	Location		Township	Parameters Monitored	Method /	Monitoring	Mobile
		Latitude	Longitude			Instrument	Frequency	Signal strength
1	Myohla	19° 25'	96° 17'	Yedashe	Water Level	Ordinary	Daily	
2	Ohnpin	18° 49'	96° 26'	Oaktwin	Water Level	Ordinary	Daily	
3	Byatkale	18° 41'	96° 27'	Oaktwin	Water Level	Ordinary	Daily	
4	Zalokegyi	18° 36'	96° 31'	Phyu	Water Level	Ordinary	Daily	
5	Thaungbu	18° 31'	96° 35'	Phyu	Water Level	Ordinary	Daily	
6	Kwinchaungwa	18° 14'	96° 41'	Penwegone	Water Level	Ordinary	Daily	Poor
7	Innpalwe	17° 55'	96° 51'	Nyaunglebin	Water Level	Ordinary	Daily	
8	Thuyethamein	17° 46'	96° 53'	Waw	Water Level	Tidal	Daily	
9	Mingalun	17° 39' 45"	96° 45' 24"	Daik-U	Water Level	Tidal	Daily	
10	Kyaikhtawpalaing	17° 38'	96° 47'	Daik-U	Water Level	Tidal	Daily	Poor
11	Mokkhamu	17° 51'	96° 52'	Nyaunglebin	Water Level	Tidal	Daily	Poor

A

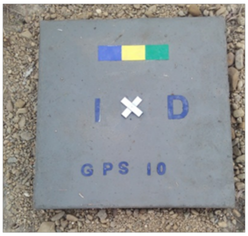
A.2. LOCATION MAP OF IWUMD WATER LEVEL GAUGE STATIONS.



A.3. LOCATION MAP OF RIVER CROSS-SECTION POINTS.



A.4. INSTALLATION OF PERMANENT BENCHMARKS.



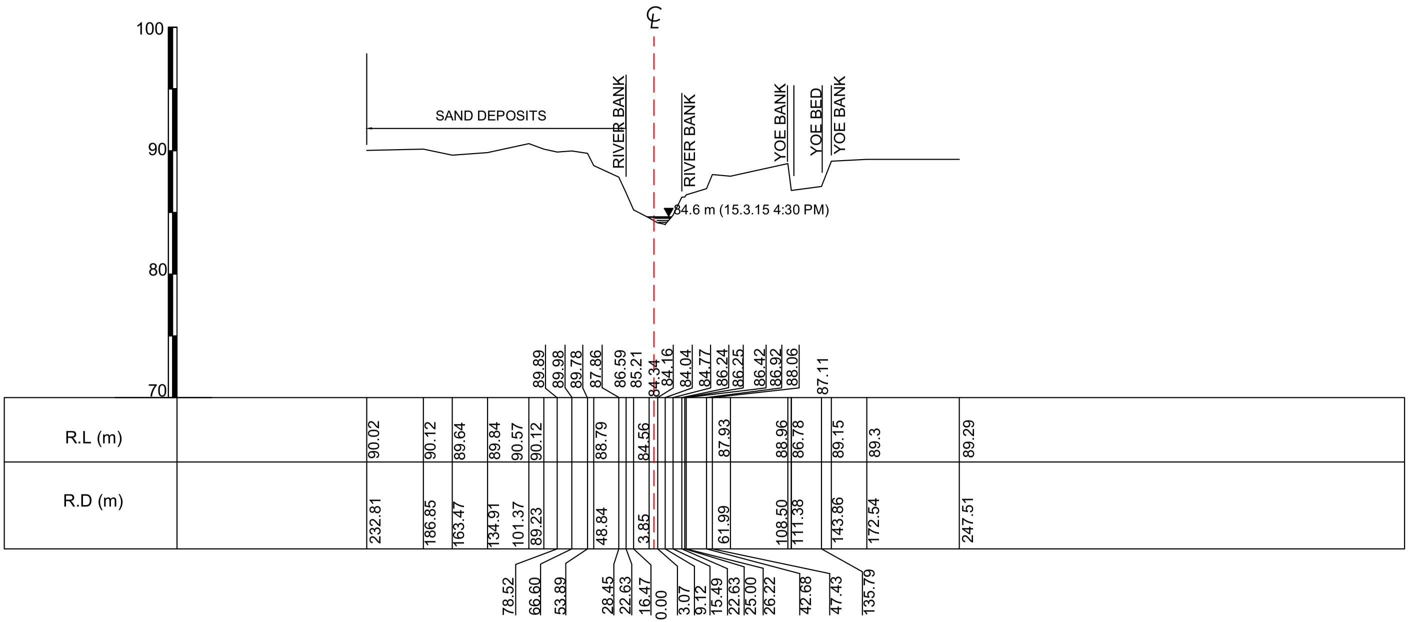
A.5. CROSS-SECTIONS OF THE SITTAUNG RIVER.

SHEET 1

CROSS SECTION OF SITTAUNG RIVER

SECTION (CS 1) NEAR THAR YA GONE VILLAGE, PYINMANA TOWNSHIP

Vertical scale 1 cm : 3.5 m
Horizontal scale 1 cm : 35 m

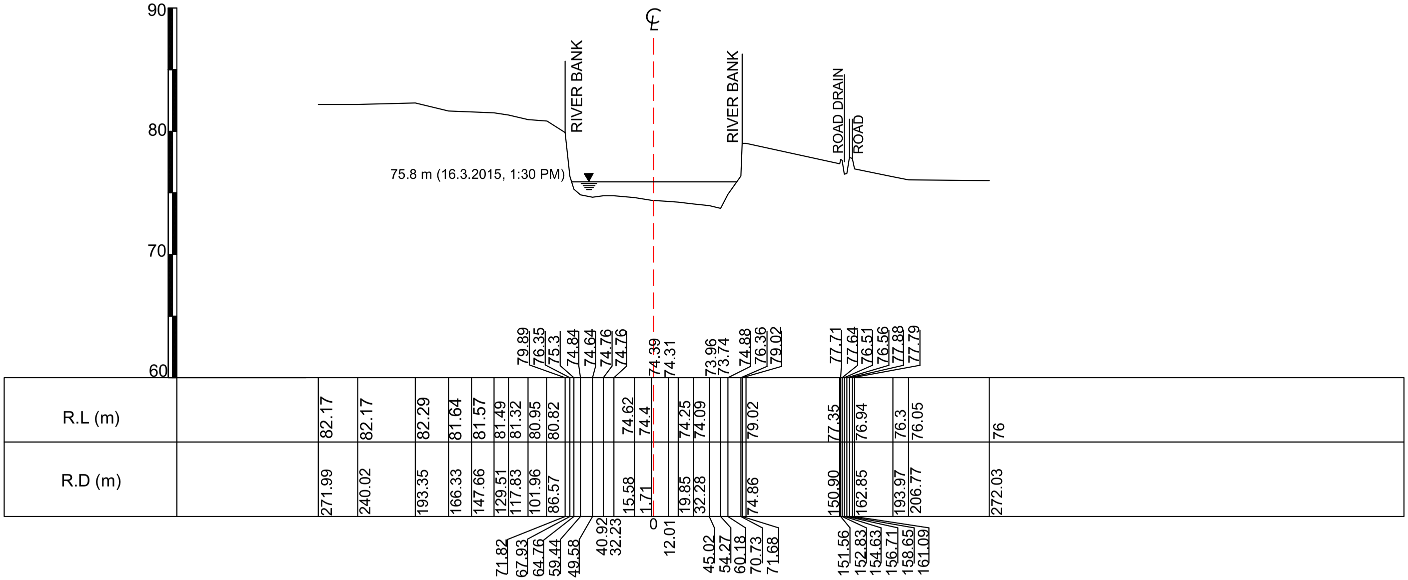


SHEET 2

CROSS SECTION OF SITTAUNG RIVER

SECTION (CS2) NEAR ZEE PHYU PIN VILLAGE, PYINMANA TOWNSHIP

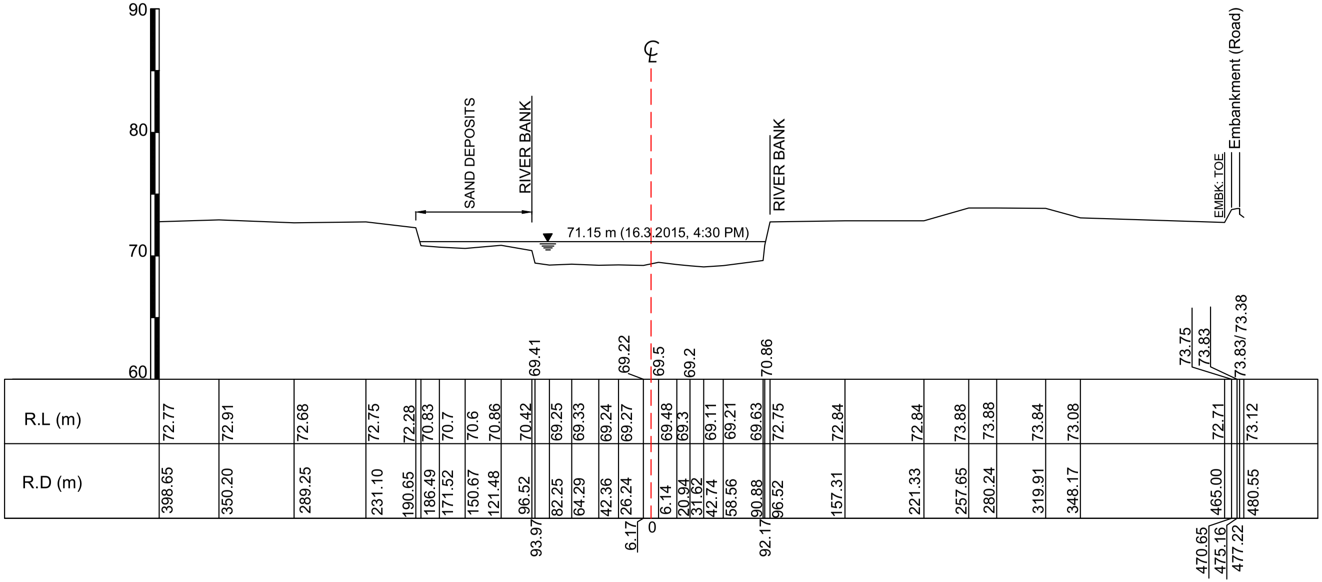
Vertical scale 1 cm : 3.5 m
Horizontal scale 1 cm : 35 m



CROSS SECTION OF SITTAUNG RIVER

SECTION (CS 3) NEAR YAE KAR VILLAGE, LEWE TOWNSHIP

Vertical scale 1 cm : 3.5 m
Horizontal scale 1 cm : 35 m

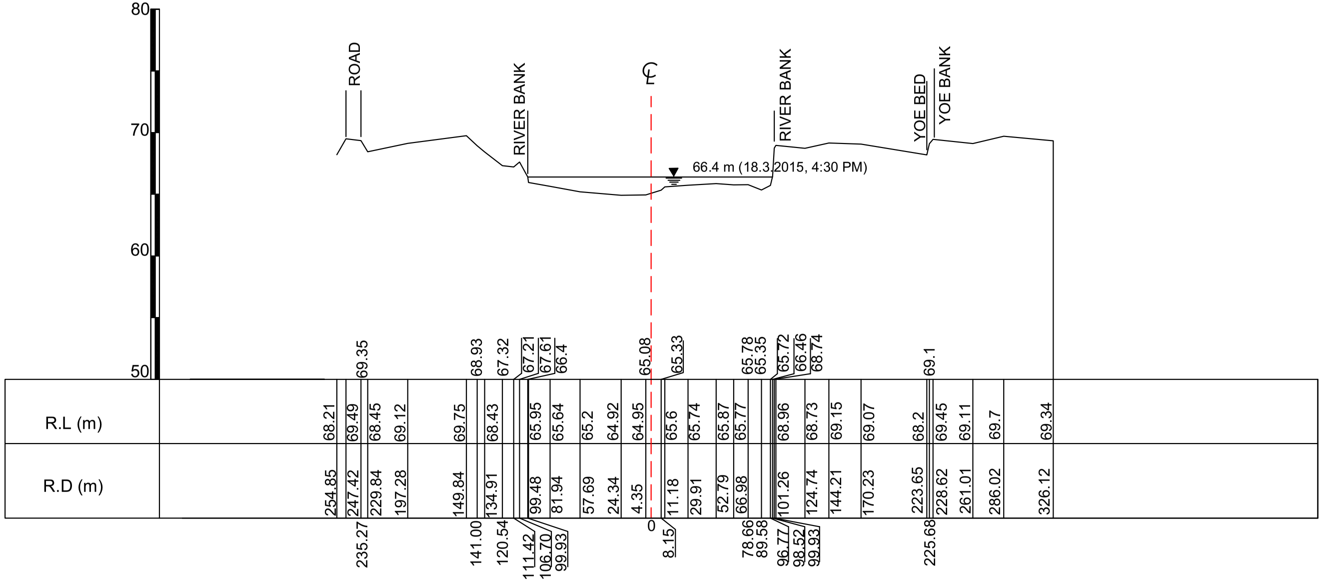


SHEET 4

CROSS SECTION OF SITTAUNG RIVER

SECTION (CS 4) NEAR YE NI LAY VILLAGE, LEWE TOWNSHIP

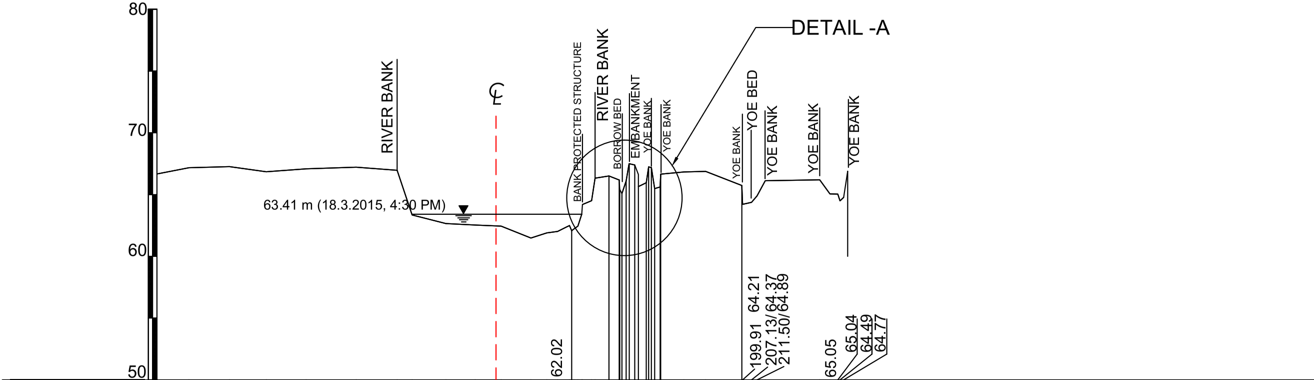
Vertical scale 1 cm : 3.5 m
Horizontal scale 1 cm : 35 m



CROSS SECTION OF SITTAUNG RIVER

SECTION (CS4B) NEAR MYO HLA VILLAGE, YADASHE TOWNSHIP

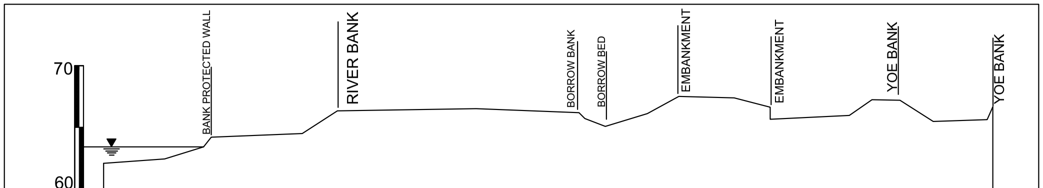
Vertical scale 1 cm : 3.5 m
Horizontal scale 1 cm : 35 m



R.D (m)	R.L (m)
274.90	66.67
248.93	67.18
216.08	67.26
186.25	66.85
154.03	67.09
113.41	67.22
80.25	66.97
68.01	63.35
40.68	62.65
16.94	62.54
0	62.47
4.14	62.45
28.24	61.49
41.19	61.9
49.82	
59.54	62.49
152.24	66.83
169.90	66.87
199.19	65.73
218.25	66.12
262.37	66.2
285.10	66.89

61.30	62.08
63.15	62.22
66.26	62.44
69.41	63.41
70.03	64.2
77.41	64.5
80.25	66.33
91.50	66.51
99.85	66.18
100.32	65.71
101.98	65.08
105.38	66.11
107.93	67.5
112.42	67.39
115.34	66.63
115.34	65.65
121.75	65.96
123.60	67.24
125.87	67.19
128.56	65.48
132.94	65.62
133.40	66.66

DETAIL - A (Horizontal & Vertical Scale; 1 cm : 3.5 m)



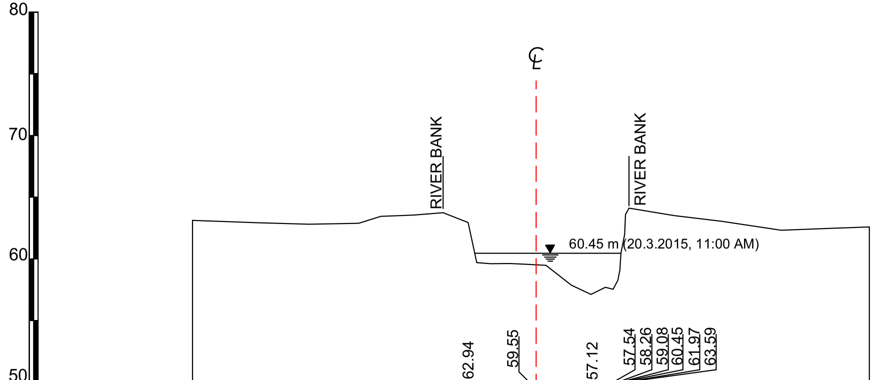
R.L (m)	R.D (m)
62.08	61.30
62.22	63.15
62.44	66.26
63.41	69.41
64.2	70.03
64.5	77.41
66.33	80.25
66.51	91.50
66.18	99.85
65.71	100.32
65.08	101.98
66.11	105.38
67.5	107.93
67.39	112.42
66.63	115.34
65.65	
65.96	121.75
67.24	123.60
67.19	125.87
65.48	128.56
65.62	132.94
66.66	133.40

SHEET 6

CROSS SECTION OF SITTAUNG RIVER

SECTION (CS 5) NEAR CHON INN VILLAGE, YADASHE TOWNSHIP

Vertical scale 1 cm : 3.5 m
Horizontal scale 1 cm : 35 m

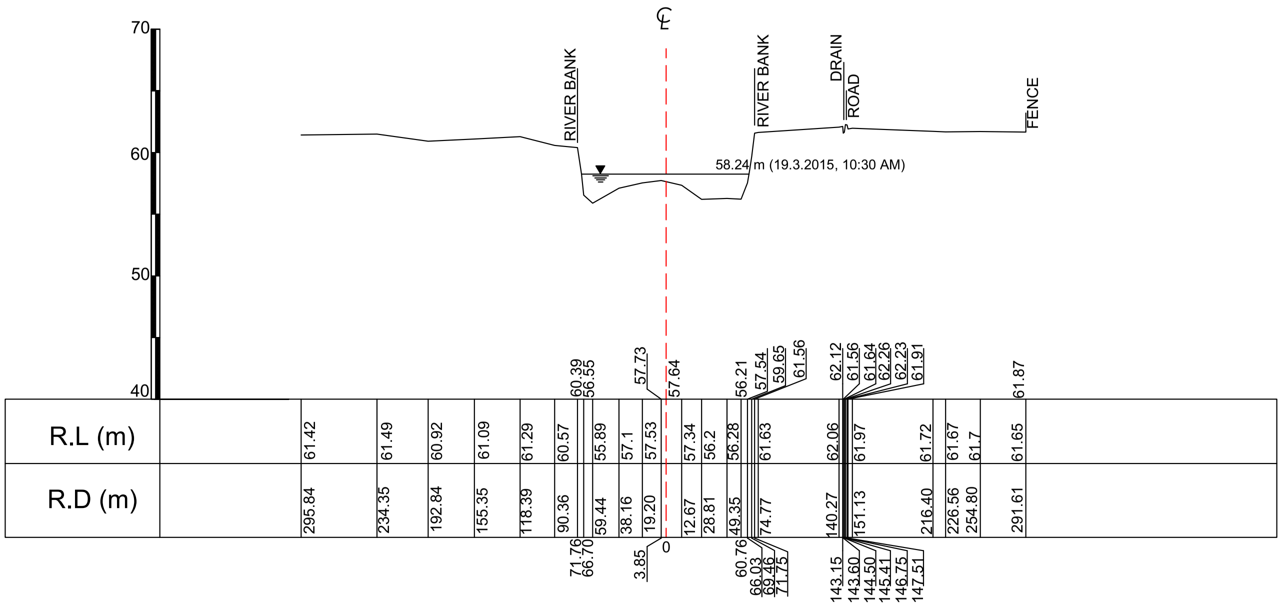


R.L (m)	R.D (m)
63.12	278.48
62.93	225.62
62.81	184.36
62.89	143.86
63.44	125.85
63.55	99.14
63.74	75.31
62.94	55.06
59.7	48.11
59.61	37.10
59.62	21.11
59.55	5.42
	0
59.48	8.08
57.88	28.59
57.12	44.47
57.69	56.21
57.54	62.43
58.26	66.36
59.08	68.00
60.45	68.82
61.97	71.82
63.59	72.54
64.12	75.31
63.51	112.12
63.05	150.53
62.32	198.72
62.45	233.21
62.59	270.22

CROSS SECTION OF SITTAUNG RIVER

SECTION (CS 5B) NEAR SWAR WA PAUK VILLAGE, YEDASHE TOWNSHIP

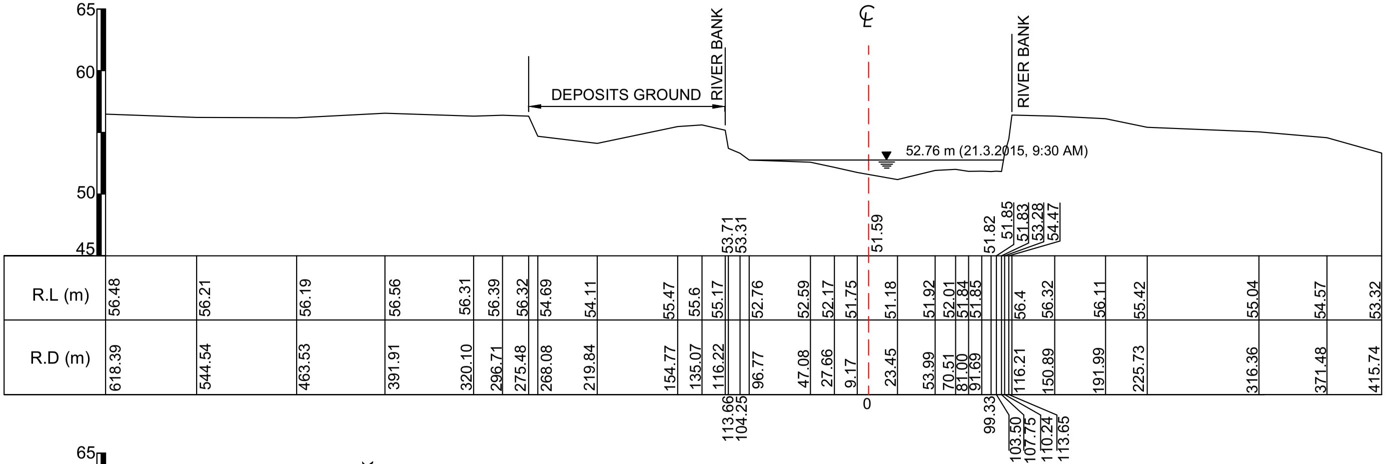
Vertical scale 1 cm : 3.5 m
Horizontal scale 1 cm : 35 m

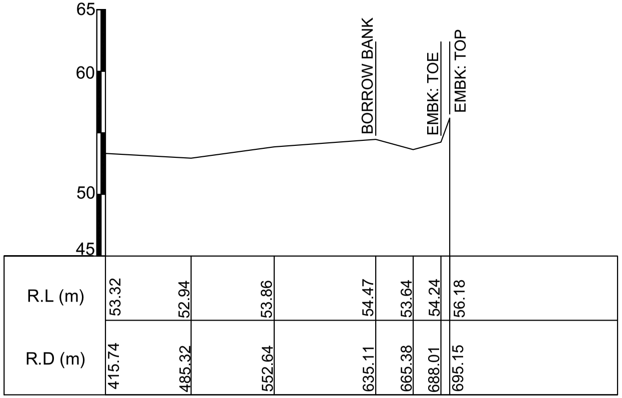


CROSS SECTION OF SITTAUNG RIVER

SECTION (CS 6) NEAR THAR YAR KONE VILLAGE, YEDASHE TOWNSHIP

Vertical scale 1 cm : 3.5 m
Horizontal scale 1 cm : 35 m

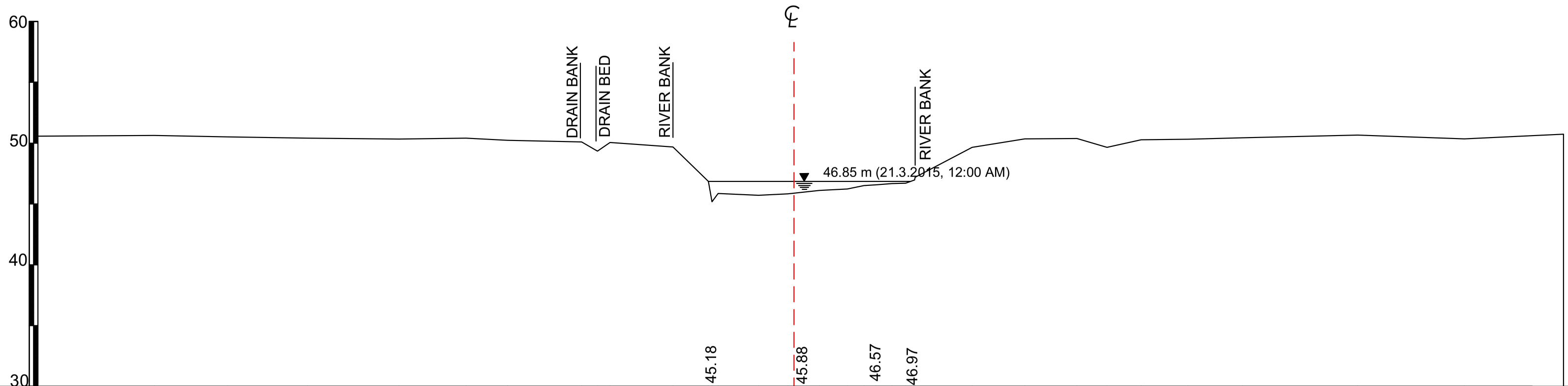




CROSS SECTION OF SITTAUNG RIVER

SECTION (CS 7) NEAR OHN PIN KWAYT VILLAGE, YEDASHE TOWNSHIP

Vertical scale 1 cm : 3.5 m
Horizontal scale 1 cm : 35 m

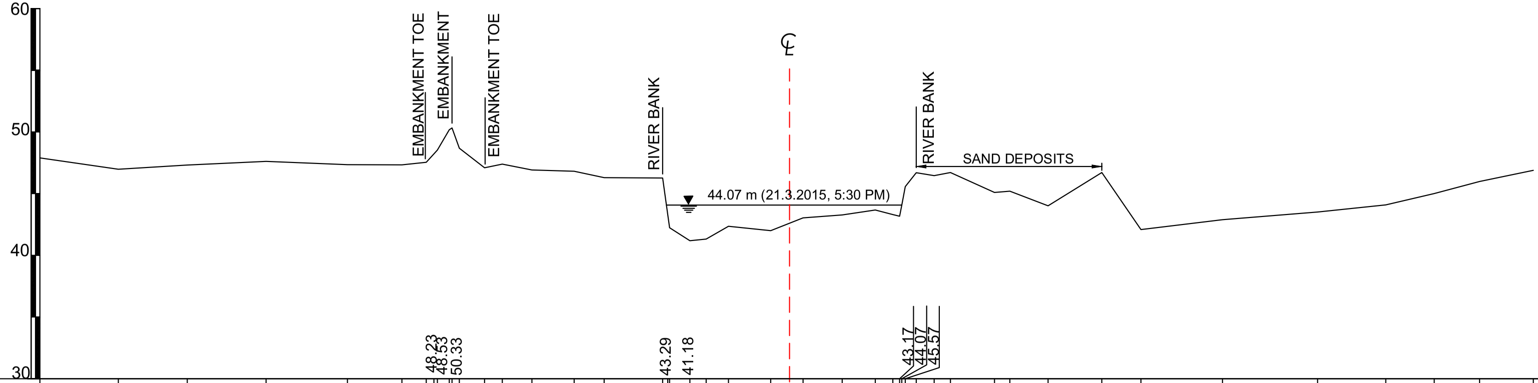


R.L (m)	50.58	50.63	50.51	50.42	50.34	50.41	50.23	50.1	49.34	50.06	49.69	46.85	45.87	45.72	45.83	46.11	46.23	46.51	46.68	46.71	47.2	49.65	50.35	50.39	49.66	50.28	50.33	50.44	50.67	50.36	50.74
R.D (m)	623.18	527.05	466.82	400.84	325.51	270.24	236.02	175.09	162.04	151.64	99.81	70.54	62.50	29.17	5.09	21.05	44.03	57.76	80.67	92.00	99.81	146.85	190.25	233.19	257.88	286.15	324.67	369.59	464.48	552.58	634.21

CROSS SECTION OF SITTAUNG RIVER

SECTION (CS 7B) NEAR SIN YWAR LAY VILLAGE, TAUNGOO TOWNSHIP

Vertical scale 1 cm : 3.5 m
Horizontal scale 1 cm : 35 m



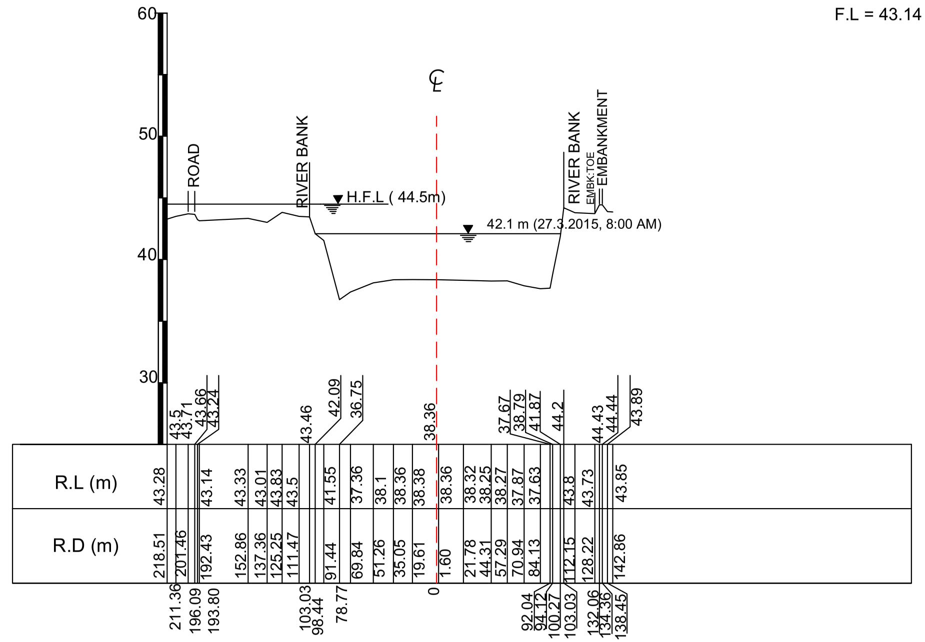
R.D (m)	R.L (m)
607.50	47.89
543.84	46.98
488.09	47.32
424.21	47.61
358.22	47.35
314.11	47.33
294.29	47.54
288.12	48.23
285.35	48.53
275.76	50.18
273.49	50.33
267.52	48.68
247.07	47.1
232.78	47.39
208.66	46.92
174.47	46.82
150.21	46.3
102.70	46.27
98.58	43.29
97.20	42.24
80.73	41.18
67.55	41.32
49.44	42.35
15.14	42
0	42.6
11.00	43.04
42.69	43.28
69.51	43.67
83.78	43.31
89.27	43.17
91.05	44.07
93.94	45.57
102.70	46.7
117.31	46.46
130.40	46.71
166.21	45.1
178.56	45.2
209.53	44.01
253.08	46.71
284.83	42.09
350.93	42.89
428.04	43.51
483.26	44.09
522.55	45.01
559.30	45.98
602.78	46.89

CROSS SECTION OF SITTAUNG RIVER

SECTION (CS 8) NEAR TAUNGOO TOWN, TAUNGOO TOWNSHIP

Vertical scale 1 cm : 3.5 m
Horizontal scale 1 cm : 35 m

H.F.L = 44.5 m
F.L = 43.14 m



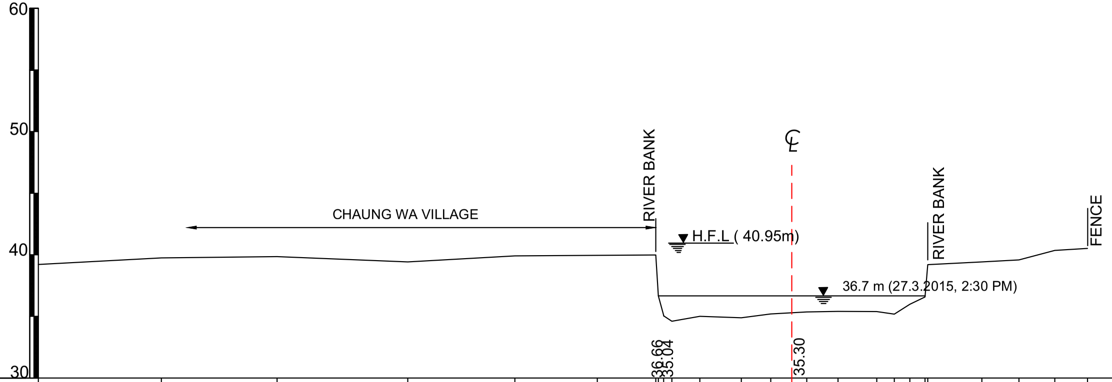
SHEET 12

CROSS SECTION OF SITTAUNG RIVER

SECTION (CS 8B) NEAR BANT BWAY PIN VILLAGE, TAUNGOO TOWNSHIP

Vertical scale 1 cm : 3.5 m
Horizontal scale 1 cm : 35 m

H.F.L = 40.95 m
F.L = 40.36 m



R.L (m)	39.22	39.75	39.85	39.42	39.91	39.95	39.99	36.66	35.04	34.61	35	34.88	35.2	35.30	35.36	35.4	35.39	35.19	35.98	36.58	39.2	39.42	39.58	40.36	40.52
R.D (m)	610.87	511.15	417.31	311.36	224.59	157.75	110.25	108.28	103.86	97.33	74.63	40.90	17.10	0	12.02	37.43	68.84	83.05	95.60	108.02	110.25	154.00	184.04	213.16	239.64

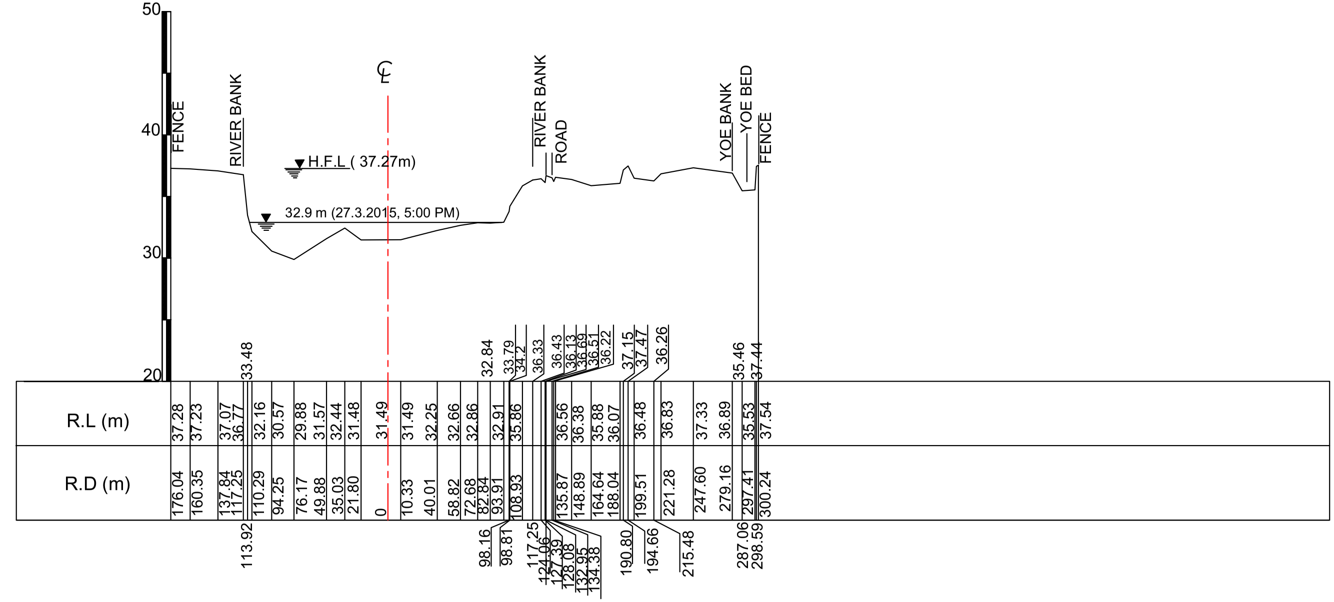
SHEET 13

CROSS SECTION OF SITTAUNG RIVER

SECTION (CS 9) NEAR OHN PIN VILLAGE, OKTWIN TOWNSHIP

Vertical scale 1 cm : 3.5 m
Horizontal scale 1 cm : 35 m

H.F.L = 37.27 m
F.L = 36.11 m

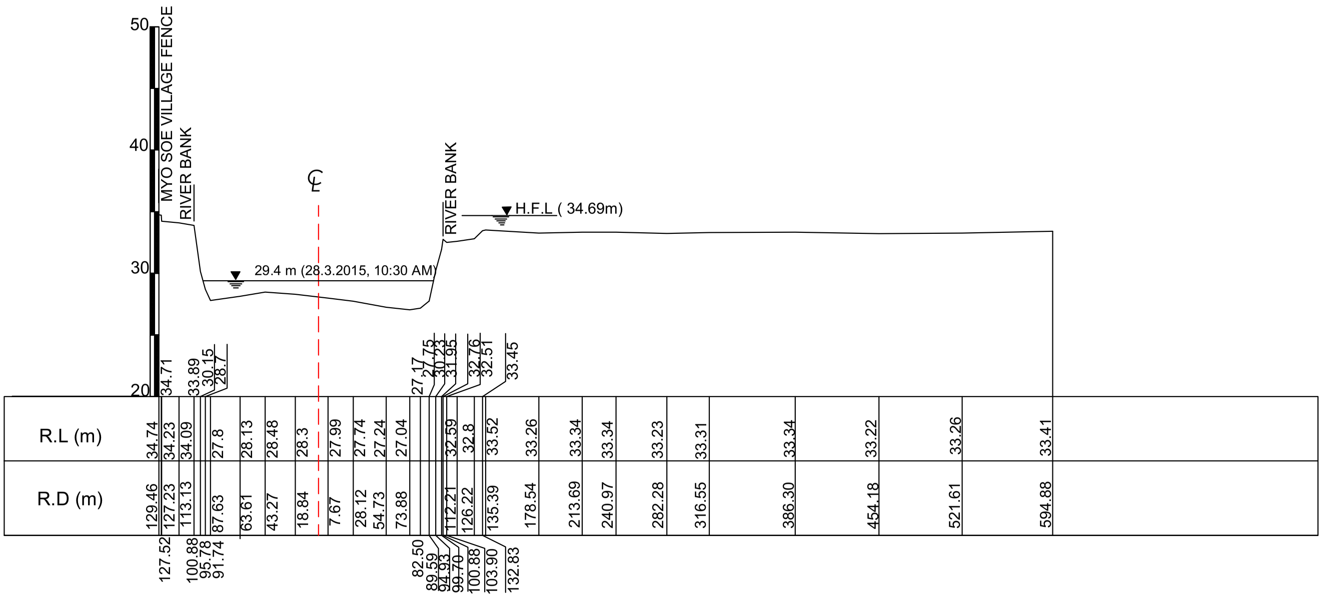


CROSS SECTION OF SITTAUNG RIVER

SECTION (CS 10) NEAR BYET KA LAY VILLAGE, OKTWIN TOWNSHIP

Vertical scale 1 cm : 3.5 m
Horizontal scale 1 cm : 35 m

H.F.L = 34.69 m
F.L = 31.95 m



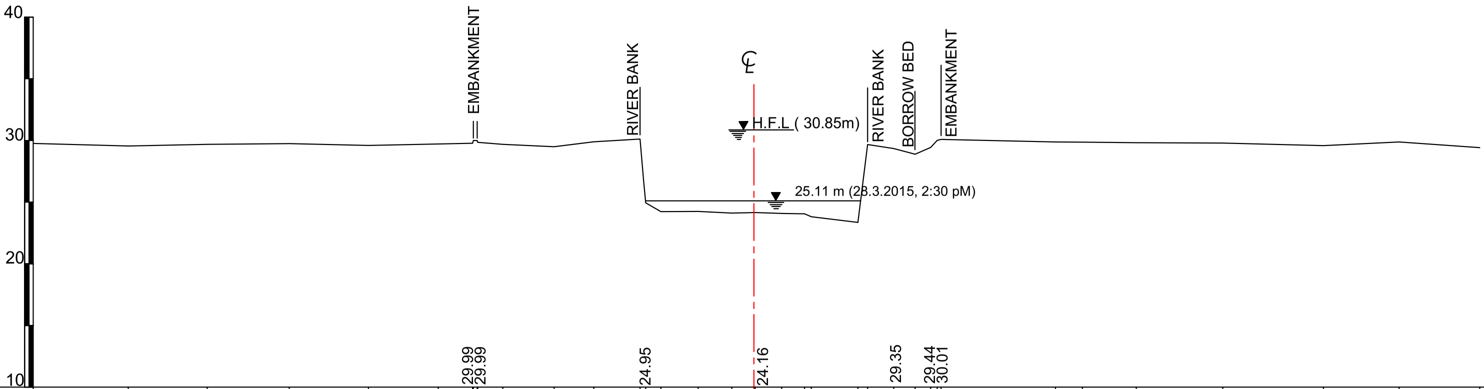
SHEET 15

CROSS SECTION OF SITTAUNG RIVER

SECTION (CS 10B) NEAR ZA LOKE GYI VILLAGE, PHYU TOWNSHIP

Vertical scale 1 cm : 3.5 m
Horizontal scale 1 cm : 35 m

H.F.L = 30.85 m
F.L = 29.5 m



R.L (m)	29.76	29.55	29.68	29.74	29.59	29.71	29.77	29.85	29.68	29.49	29.89	30.12	24.23	24.25	24.12	24.16	24.09	24.05	23.82	23.35	29.67	28.89		30.09	29.88	29.87	29.82	29.79	29.58	29.88	29.42
R.D (m)	584.16	507.22	443.18	376.56	312.43	255.90	228.02	223.89	203.53	161.87	129.84	92.26	75.45	45.20	17.93	0	22.57	41.10	46.55	84.38	92.26	130.68	143.33	151.78	244.52	266.26	310.08	380.06	461.82	523.16	588.41

227.42
224.34
87.68
1.05
113.40
148.61

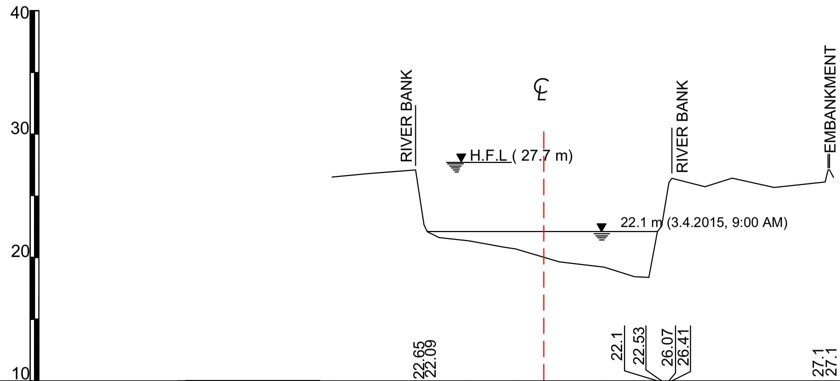
SHEET 16

CROSS SECTION OF SITTAUNG RIVER

SECTION (CS 11) NEAR KYAR INN (UPPER) VILLAGE, PHYU TOWNSHIP

Vertical scale 1 cm : 3.5 m
Horizontal scale 1 cm : 35 m

H.F.L = 27.7 m
F.L = 26.4 m



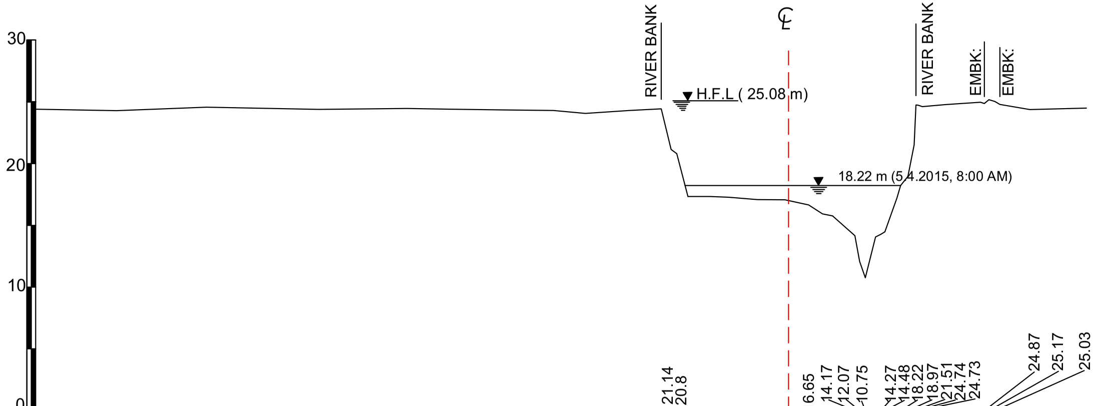
R.D (m)	R.L (m)
171.62	26.52
142.04	26.8
103.96	27.1
97.07	22.65
94.46	22.09
85.04	21.61
60.68	21.35
31.91	20.83
22.89	20.69
0	10.02
12.62	19.65
49.15	19.21
73.61	18.44
85.22	18.39
92.29	22.1
95.66	22.53
101.50	26.07
103.96	26.41
107.51	26.32
130.81	25.73
152.84	26.43
186.95	25.67
228.21	26.12
230.65	27.1
231.86	27.1
235.01	26.49

CROSS SECTION OF SITTAUNG RIVER

SECTION (CS 11B) NEAR SAY YOE KONE VILLAGE, PHYU TOWNSHIP

Vertical scale 1 cm : 3.5 m
Horizontal scale 1 cm : 35 m

H.F.L = 25.08 m
F.L = 24.82 m



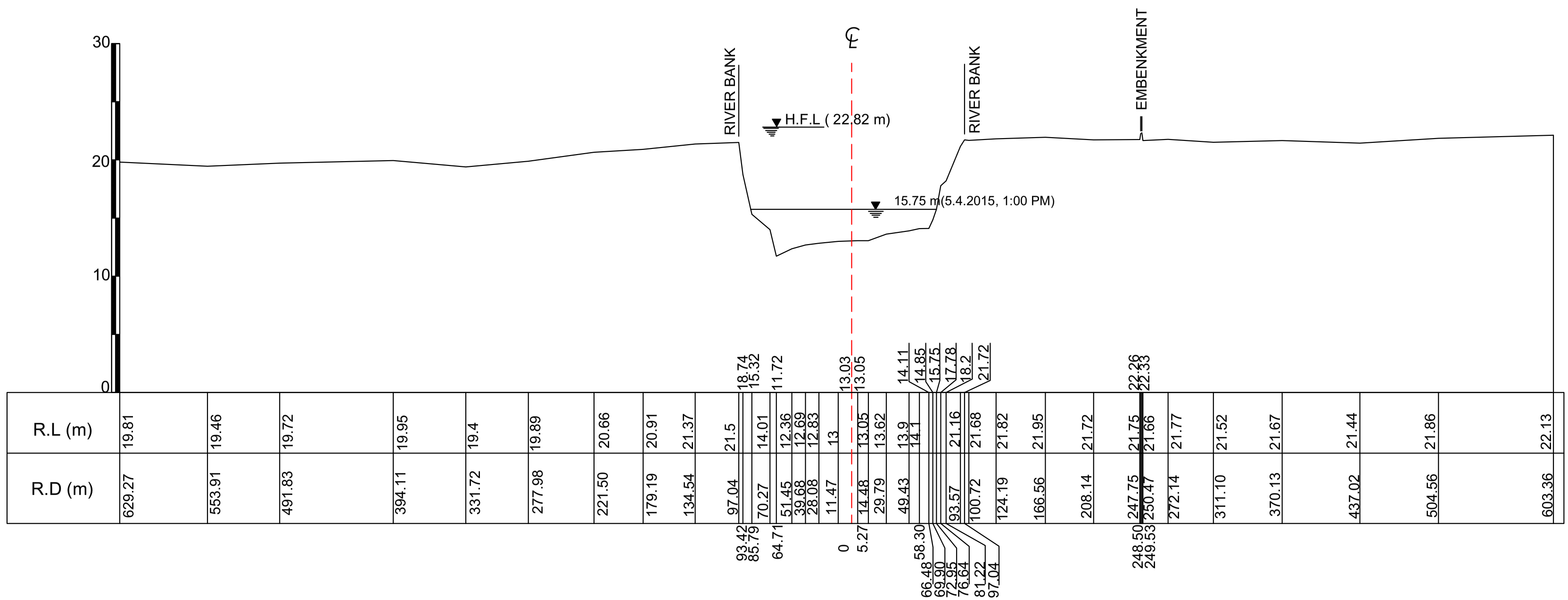
R.L (m)	R.D (m)
24.41	610.13
24.29	544.59
24.56	471.64
24.39	380.88
24.47	309.23
24.41	273.98
24.35	230.57
24.3	190.58
24.06	164.64
24.3	128.86
24.44	103.21
21.14	95.17
20.8	90.57
17.34	81.52
17.34	63.58
17.27	48.41
17.09	25.07
17.07	2.77
17.01	0
16.65	16.33
15.93	27.55
15.77	35.63
14.17	53.78
12.07	57.58
10.75	62.16
14.06	70.49
14.27	74.70
14.48	78.01
17.22	87.83
18.22	90.80
18.97	96.76
21.51	101.77
24.74	103.21
24.73	105.09
24.61	108.42
24.77	126.84
24.97	155.55
24.87	158.61
25.17	162.36
25.03	167.25
24.79	171.24
24.38	195.64
24.49	241.42

CROSS SECTION OF SITTAUNG RIVER

SECTION (CS 12) NEAR MYA PA GOE VILLAGE, PHYU TOWNSHIP

Vertical scale 1 cm : 3.5 m
Horizontal scale 1 cm : 35 m

H.F.L = 22.82 m
F.L = 20.91 m

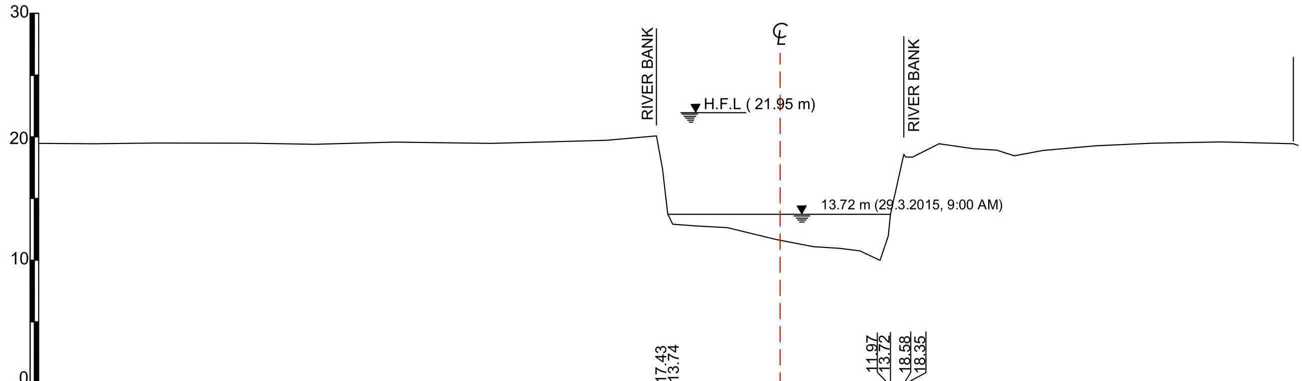


CROSS SECTION OF SITTAUNG RIVER

SECTION (CS 12B) NEAR AH NAN BAW VILLAGE, PHYU TOWNSHIP

Vertical scale 1 cm : 3.5 m
Horizontal scale 1 cm : 35 m

H.F.L = 21.95 m
F.L = 19.95 m



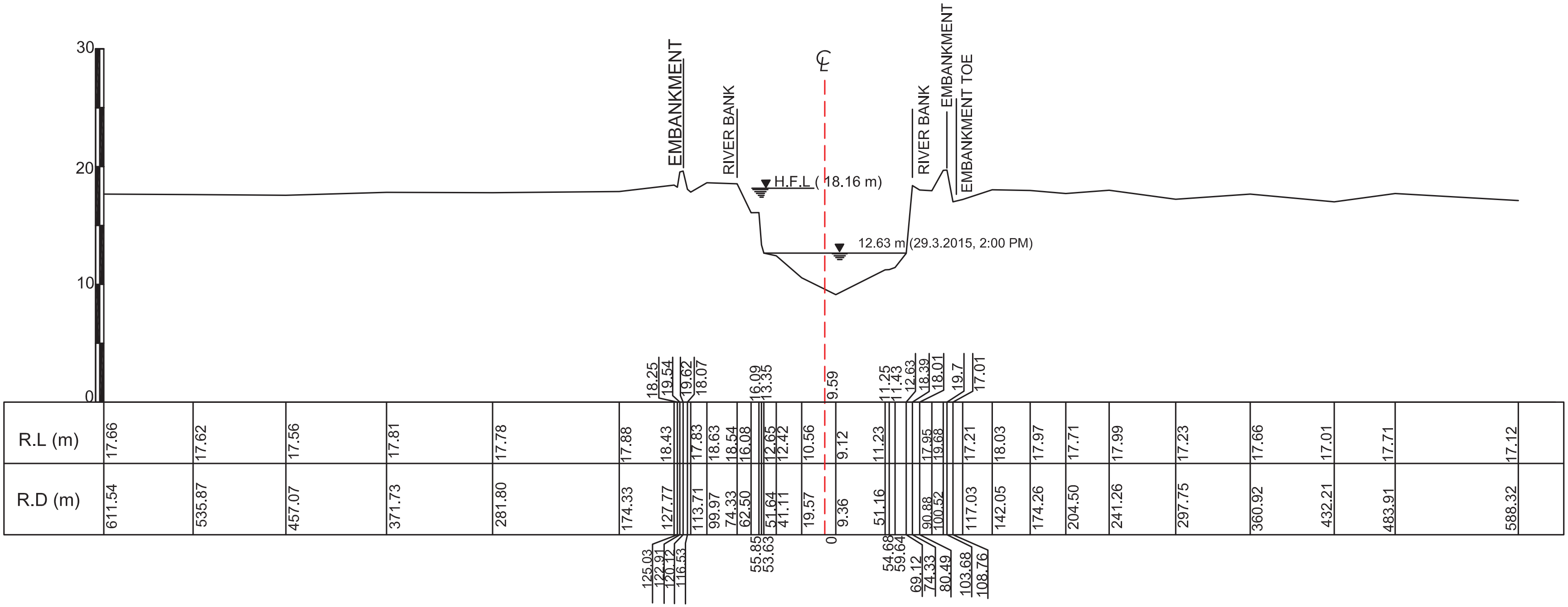
R.L (m)	R.D (m)
19.47	601.38
19.44	556.21
19.5	505.76
19.48	428.97
19.39	377.82
19.57	312.56
19.47	234.41
19.59	189.39
19.72	140.47
20.07	100.32
17.43	95.43
13.74	91.23
12.92	87.15
12.77	67.20
12.63	42.70
11.68	3.73
11.61	0
11.1	26.90
10.96	48.05
10.75	64.74
9.98	81.02
11.97	87.71
13.72	89.47
18.58	100.32
18.35	101.70
18.35	107.35
19.43	128.84
19.03	156.53
18.91	175.48
18.46	189.96
18.89	212.94
19.27	256.24
19.48	301.37
19.59	358.00
19.44	416.17
19.3	420.10

CROSS SECTION OF SITTAUNG RIVER

SECTION (CS 13) NEAR KYAUK SA YIT VILLAGE, KYAUKTAGA TOWNSHIP

Vertical scale 1 cm : 3.5 m
Horizontal scale 1 cm : 35 m

H.F.L = 18.16 m
F.L = 17.01 m



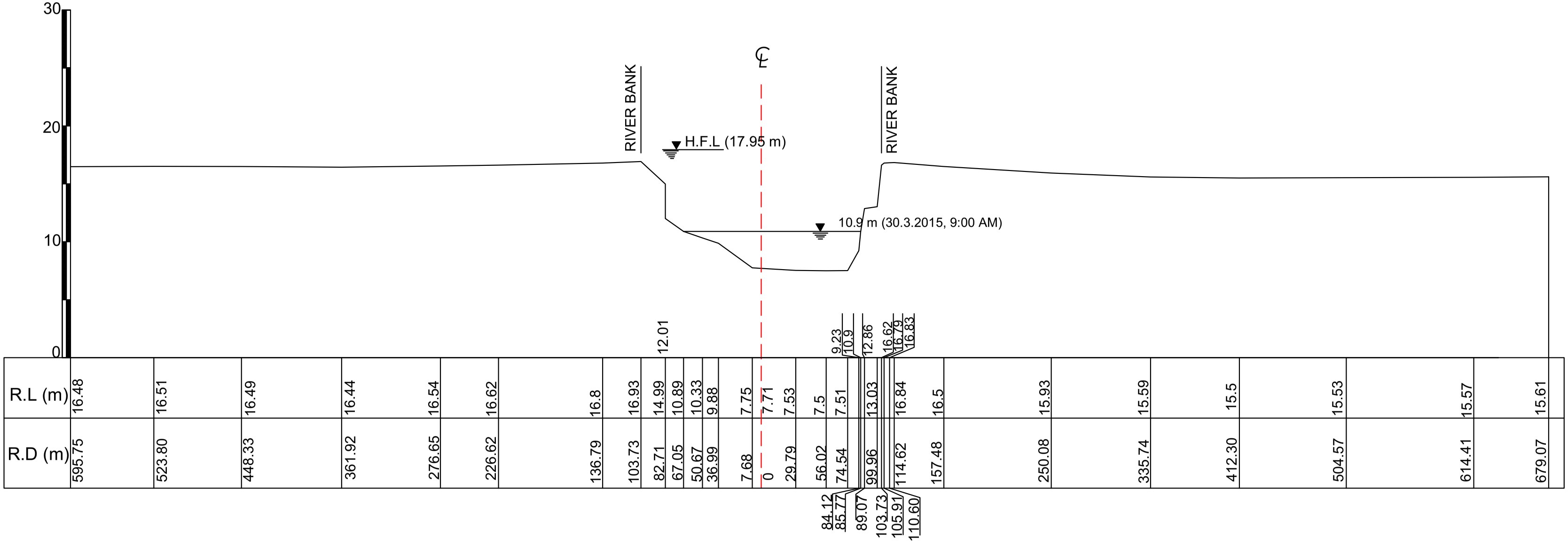
SHEET 21

CROSS SECTION OF SITTAUNG RIVER

SECTION (CS 14) NEAR KA NYIN KYOE VILLAGE, KYAUKTAGA TOWNSHIP

Vertical scale 1 cm : 3.5 m
Horizontal scale 1 cm : 35 m

H.F.L = 17.95 m
F.L = 16.83 m



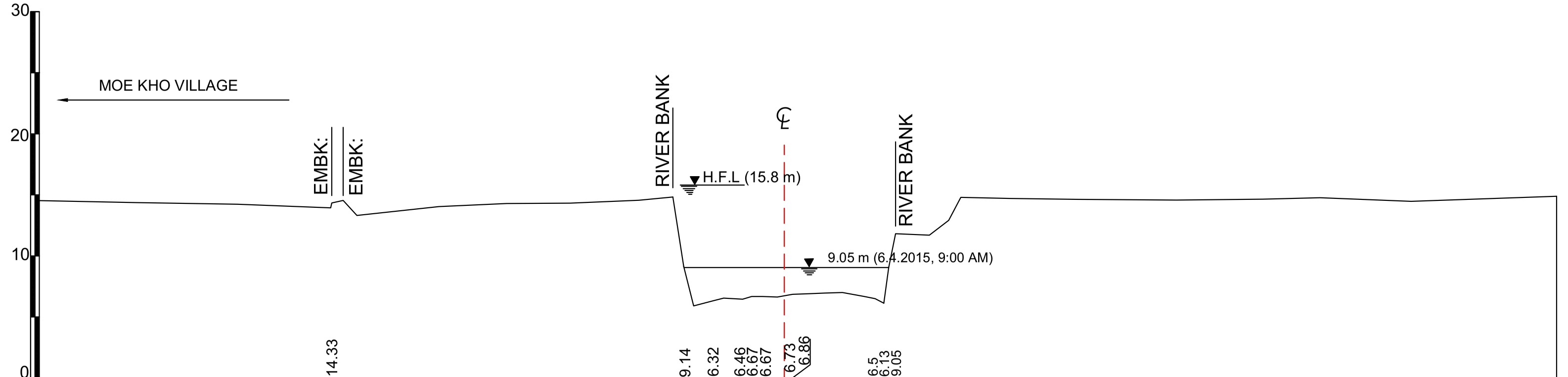
SHEET 22

CROSS SECTION OF SITTAUNG RIVER

SECTION (CS 14B) NEAR MOE KHO VILLAGE, NYAUNGLEBIN TOWNSHIP

Vertical scale 1 cm : 3.5 m
Horizontal scale 1 cm : 35 m

H.F.L = 15.8 m
F.L = 14.85 m



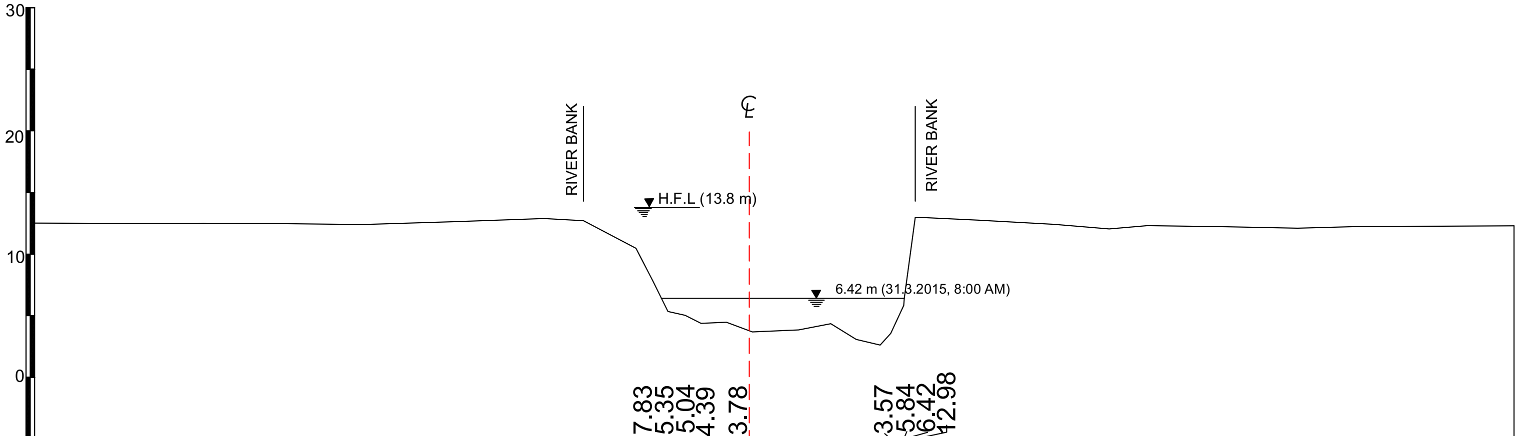
R.L (m)	R.D (m)
14.53	610.69
14.36	530.98
14.24	448.23
13.94	371.82
14.33	370.91
14.55	361.61
13.31	350.31
14.04	283.04
14.29	227.49
14.32	175.66
14.56	119.08
14.82	91.30
9.14	82.35
5.91	74.23
6.32	58.42
6.54	49.58
6.46	34.10
6.67	26.73
6.67	17.81
6.63	5.63
6.73	0
6.86	6.88
6.89	19.10
6.96	33.49
7.0	47.68
6.68	65.70
6.5	74.51
6.13	81.57
9.05	85.68
11.82	91.30
11.7	119.03
12.91	134.82
14.79	144.74
14.71	184.78
14.64	239.74
14.58	321.50
14.65	392.42
14.76	439.18
14.47	513.84
14.89	633.11

CROSS SECTION OF SITTAUNG RIVER

SECTION (CS 15) NEAR KWIN DALA VILLAGE, NYAUNGLEBIN TOWNSHIP

Vertical scale 1 cm : 3.5 m
Horizontal scale 1 cm : 35 m

H.F.L = 13.8 m
F.L = 12.85 m



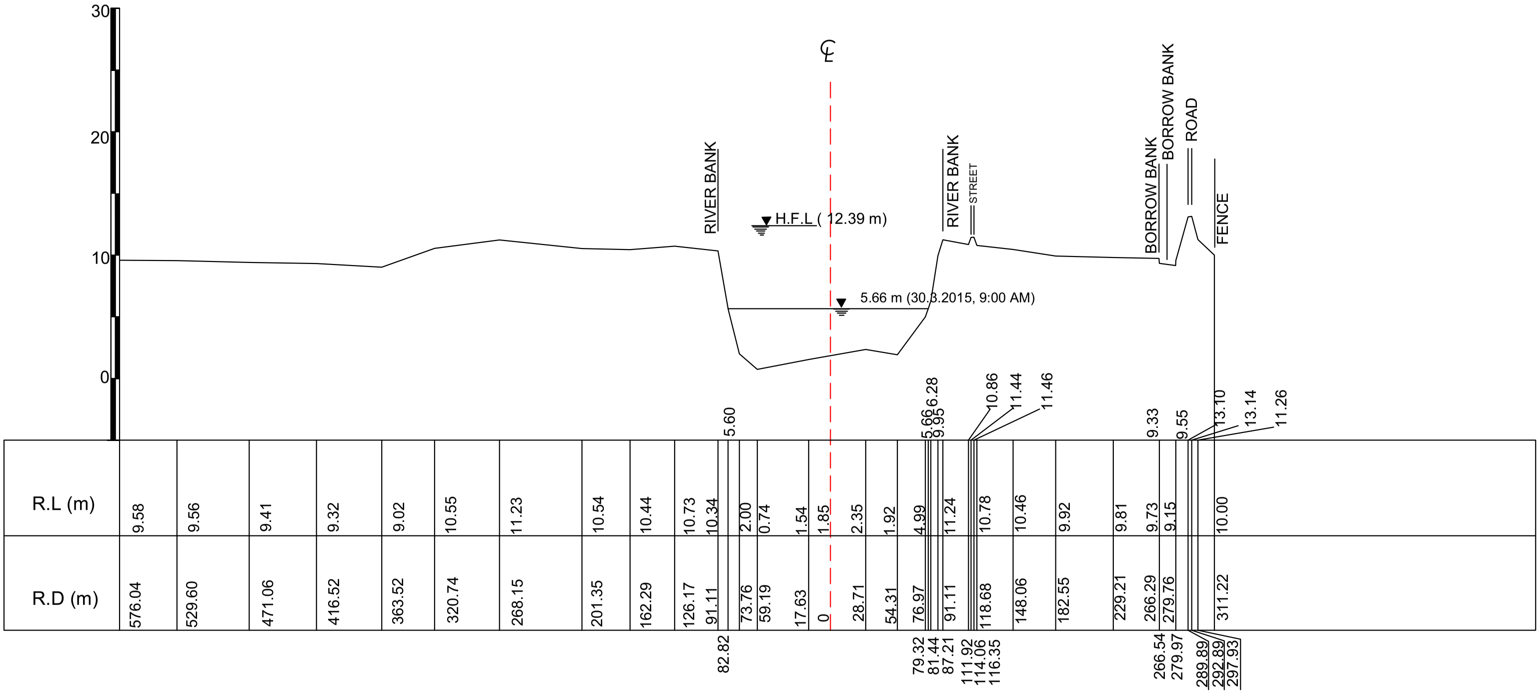
R.L (m)	12.52	12.49	12.51	12.47	12.4	12.64	12.89	12.71	10.47	7.83 5.35 5.04 4.39	4.47	3.78	3.69 3.85	4.35	3.08	2.62	3.57 5.84 6.42 12.98	12.96	12.76	12.42	12.05	12.31	12.23	12.11	12.25	12.27	12.3
R.D (m)	579.46	499.08	442.18	378.97	313.70	237.52	166.52	134.44	91.91	78.30 66.05 52.06 39.12	18.57	0	2.49	39.90	66.05	86.55	105.96 114.61 125.22 125.59 134.44	142.01	185.64	247.41	291.71	322.66	385.89	444.53	498.21	561.51	619.87

CROSS SECTION OF SITTAUNG RIVER

SECTION (CS 16) NEAR MA DAUK KALAY VILLAGE, NYAUNGLEBIN TOWNSHIP

Vertical scale 1 cm : 3.5 m
Horizontal scale 1 cm : 35 m

H.F.L = 12.39 m
F.L = 11.09 m



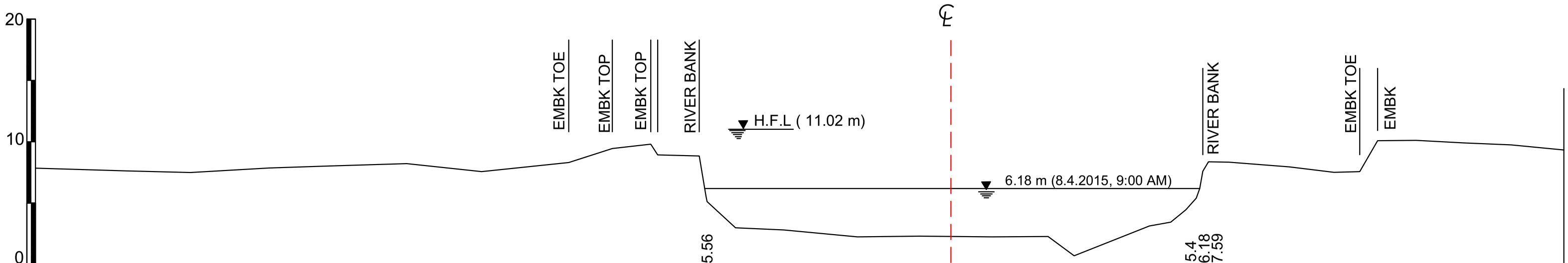
SHEET 25

CROSS SECTION OF SITTAUNG RIVER

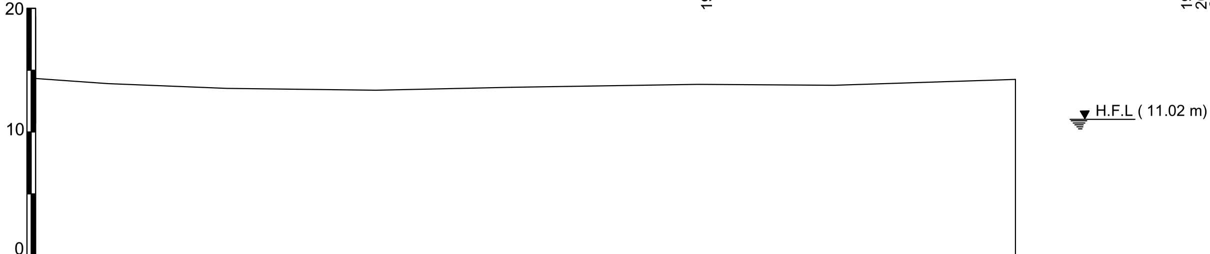
SECTION (CS17) NEAR DON ZA YIT VILLAGE, NYAUNGLEBIN TOWNSHIP

Vertical scale 1 cm : 3.5 m
Horizontal scale 1 cm : 35 m

H.F.L = 11.02 m
F.L = 9.3 m



R.L (m)	R.D (m)
7.85	744.325
7.63	670.821
7.49	618.372
7.86	554.197
8.03	505.005
8.21	442.404
7.56	381.586
8.3	310.729
9.45	275.308
9.8	244.095
8.93	238.455
8.84	204.707
5.56	198.326
5.12	199.231
2.98	175.12
2.8	135.761
2.25	75.978
2.31	25.547
2.28	0
2.24	33.143
2.27	78.894
0.71	100.15
3.14	161.422
3.45	178.741
4.45	190.941
5.4	199.376
6.18	202.215
7.59	204.706
8.36	209.308
8.33	225.95
7.95	275.192
7.5	311.52
7.56	332.324
10.09	346.907
10.11	378.196
9.9	416.64
9.74	455.525
9.33	498.37



R.L (m)	R.D (m)
9.33	498.37
8.91	557.02
8.53	653.331
8.39	774.229
8.62	884.481
8.86	1035.719
8.78	1145.743
9.25	1292.712

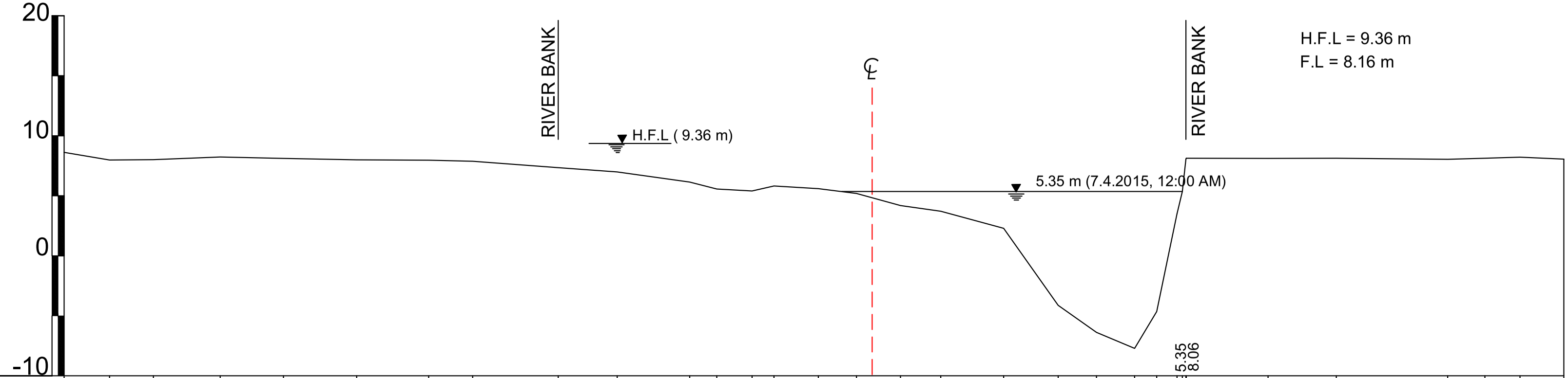
SHEET 26

CROSS SECTION OF SITTAUNG RIVER

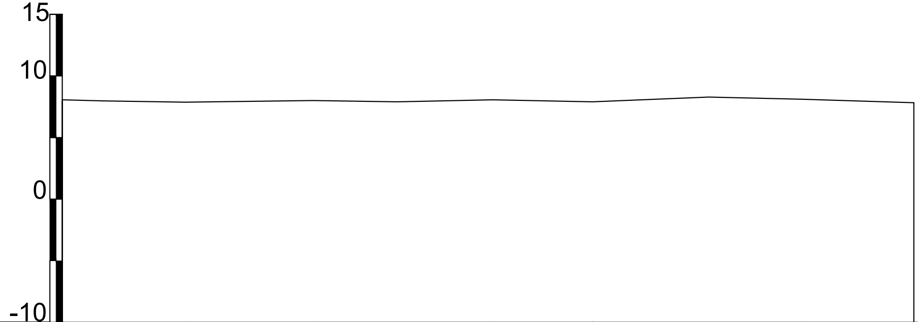
SECTION (CS18) NEAR PAN NYO SU VILLAGE, WAW TOWNSHIP

Vertical scale 1 cm : 3.5 m
Horizontal scale 1 cm : 35 m

H.F.L = 9.36 m
F.L = 8.16 m



R.L (m)	8.62	7.98	8.01	8.23	8.11	7.99	7.96	7.88	7.34	6.98	6.14	5.56	5.4	5.82	5.59	5.2	4.83	4.18	3.71	2.29	-4.13	-6.38	-7.72	-4.65	3.51	5.35	8.06	8.13	8.11	8.13	8.04	8.13	8.22	8.06
R.D (m)	671.96	634.15	597.64	542.16	489.53	428.69	368.70	332.20	260.96	211.99	151.67	129.11	99.79	81.52	44.62	13.05	0	23.66	57.05	109.47	154.82	186.56	218.27	236.76	253.54	258.05	260.96	261.34	329.24	385.99	478.69	509.59	538.83	575.35



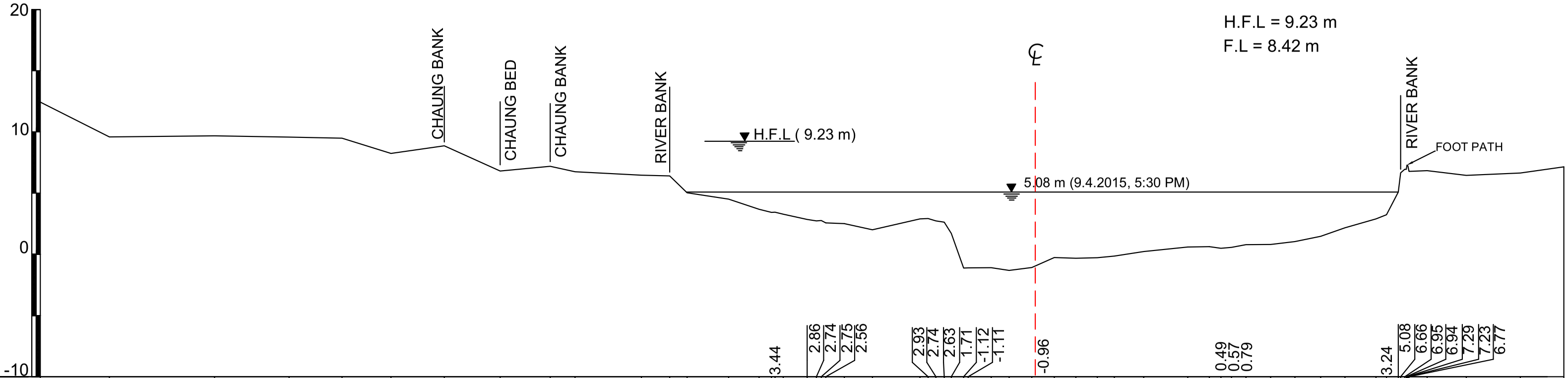
R.L (m)	8.06	7.98	7.88	8.01	7.91	8.06	7.91	8.29	8.11	7.83
R.D (m)	575.35	538.83	674.88	778.58	846.92	924.16	1005.11	1099.52	1175.61	1265.80

CROSS SECTION OF SITTAUNG RIVER

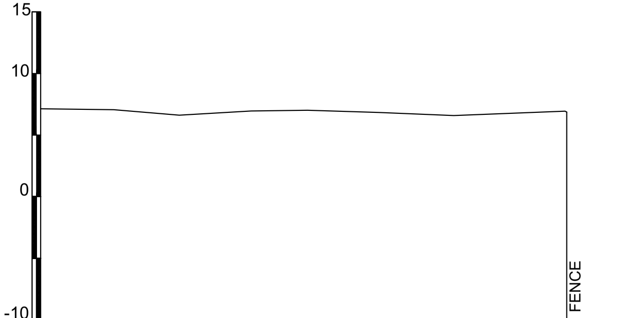
SECTION (CS 19) NEAR LET PAN VILLAGE, WAW TOWNSHIP

Vertical scale 1 cm : 3.5 m
Horizontal scale 1 cm : 35 m

H.F.L = 9.23 m
F.L = 8.42 m



R.D (m)	R.L (m)
812.92	12.43
756.54	9.59
670.51	9.68
609.71	9.57
566.47	9.49
526.33	8.24
482.76	8.86
437.26	6.81
396.25	7.19
376.02	6.75
321.78	6.47
298.61	6.4
284.44	5.02
250.53	4.51
225.57	3.68
215.57	3.43
212.56	3.44
205.83	3.27
186.39	2.86
178.81	2.74
174.82	2.75
171.06	2.56
155.94	2.50
133.05	2.01
94.14	2.89
87.52	2.93
81.12	2.74
74.25	2.63
68.60	1.71
58.39	-1.12
54.78	-1.11
36.01	-1.09
21.33	-1.32
2.70	-1.08
0	-0.96
15.62	-0.27
33.33	-0.32
50.80	-0.28
64.60	-0.14
88.63	0.23
124.74	0.60
142.30	0.63
151.87	0.49
160.43	0.57
172.26	0.79
192.46	0.81
212.31	1.05
233.26	1.47
253.09	2.17
278.48	2.89
287.11	3.24
296.65	5.08
298.61	6.66
302.02	6.95
303.31	6.94
303.89	7.29
304.51	7.23
305.40	6.77
320.26	6.83
352.35	6.45
396.39	6.64
432.01	7.14



R.D (m)	R.L (m)
432.01	7.14
491.29	7.06
544.24	6.62
602.58	6.96
648.16	7.02
705.28	6.84
766.52	6.59
856.79	6.94
858.15	6.86

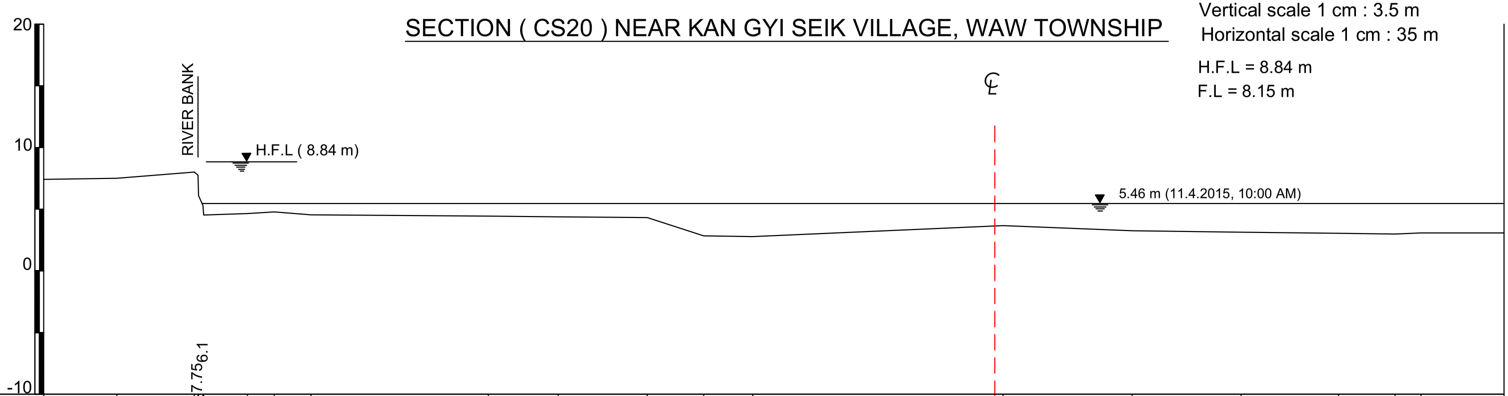
SHEET 28

CROSS SECTION OF SITTAUNG RIVER

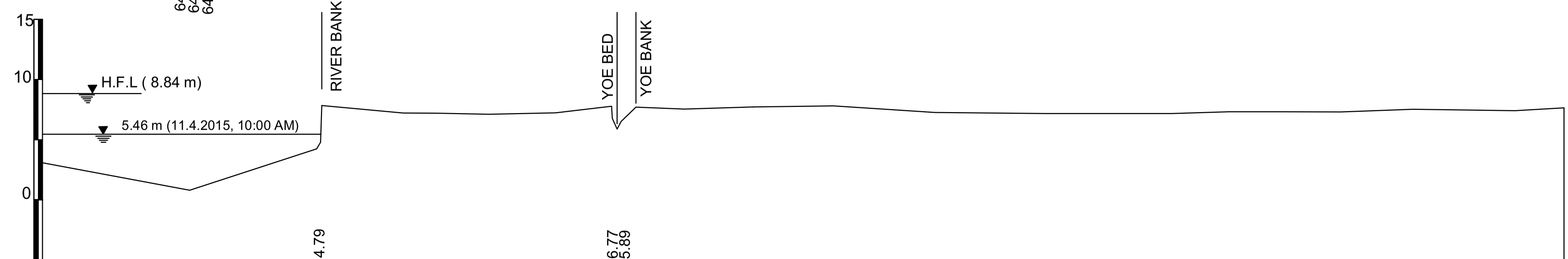
SECTION (CS20) NEAR KAN GYI SEIK VILLAGE, WAW TOWNSHIP

Vertical scale 1 cm : 3.5 m
Horizontal scale 1 cm : 35 m

H.F.L = 8.84 m
F.L = 8.15 m



R.L (m)	R.D (m)
7.42	770.80
7.51	711.47
8.01	648.61
7.75	645.65
6.1	645.26
	641.72
5.3/4.53	641.05
4.64	605.67
4.77	583.92
4.54	554.10
4.44	410.35
4.38	353.71
4.32	281.63
2.84	235.76
2.77	196.12
3.63	0
3.66	6.69
3.25	111.42
3.13	199.71
3.05	278.63
2.99	324.36
3.08	345.43
3.08	412.75



R.L (m)	R.D (m)
3.08	412.75
0.8	535.48
4.24	641.27
4.79	644.54
7.84	645.65
7.22	713.30
7.21	740.97
7.11	784.59
7.24	840.46
7.79	887.09
6.77	887.78
5.89	891.75
6.53	895.16
7.71	907.48
7.54	947.73
7.73	1004.78
7.81	1071.99
7.27	1156.67
7.18	1248.42
7.18	1354.20
7.22	1368.11
7.32	1401.64
7.33	1444.83
7.31	1494.91
7.53	1554.94
7.41	1639.94
7.65	1680.83

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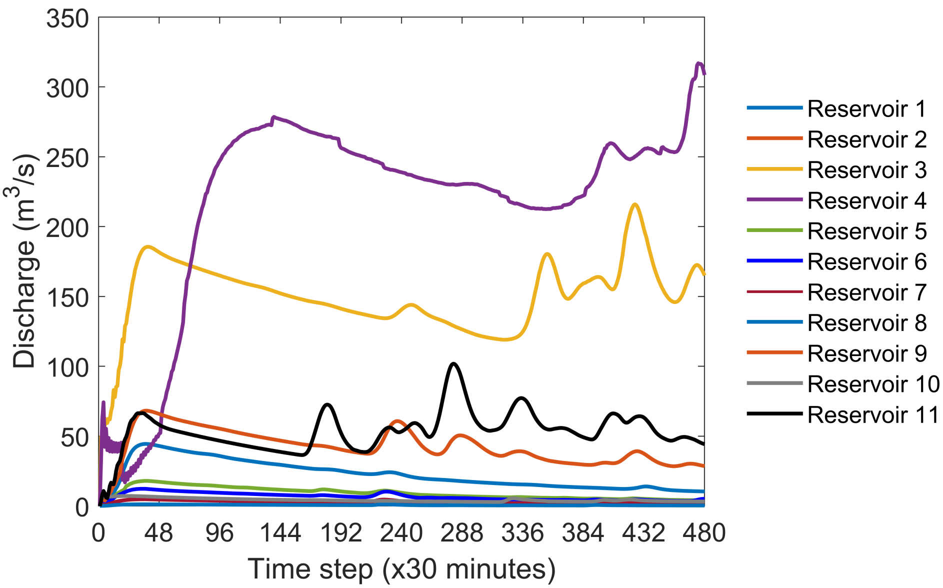
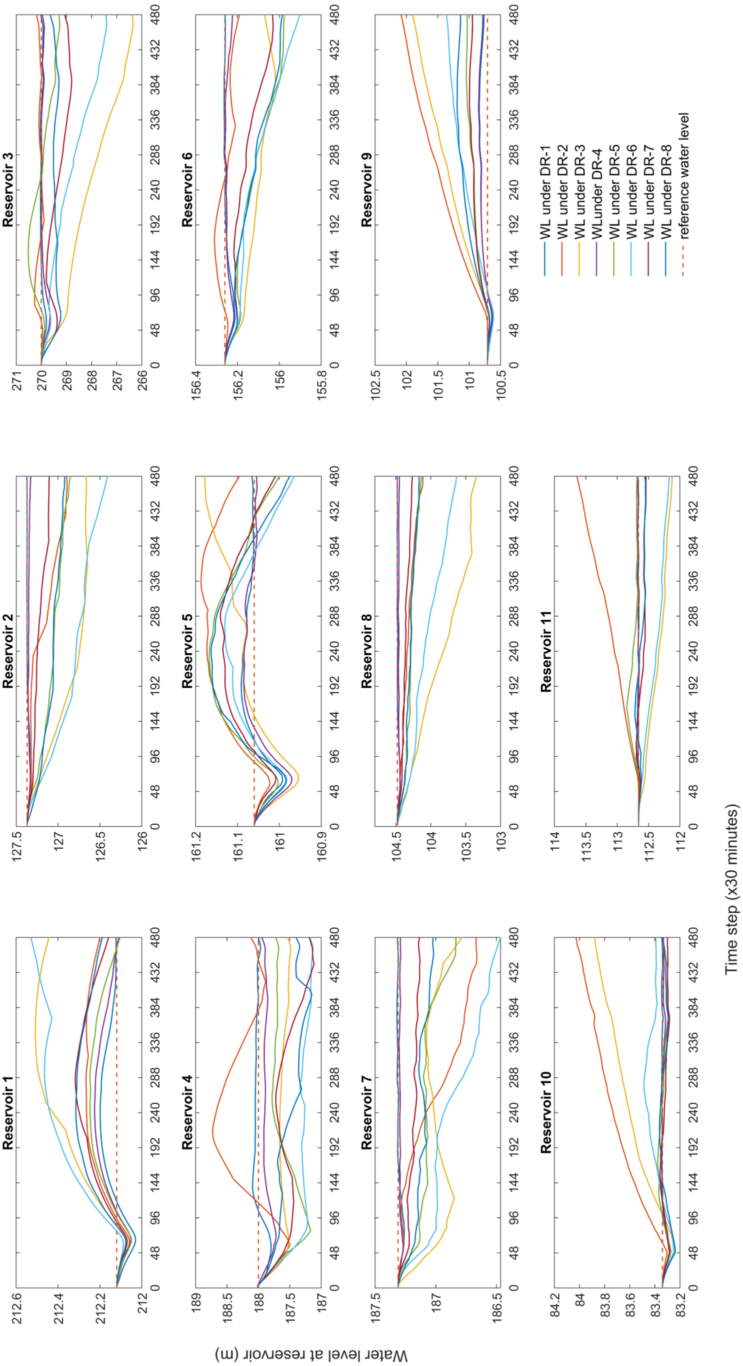
A.6. INFLOWS INTO THE RESERVOIRS (CHAPTER 5)



A.7. Reservoir water levels (Chapter 5)



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Curriculum Vitæ

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List of Publications

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4. **Myo Lin, Nay**, Tian, Xin, Rutten, Martine, Abraham, Edo, Maestre, José M. and Giesen, Nick Van De (2020): Multi-objective Model Predictive Control for Real-time Operation of a Multi-Reservoir System. *Water,* 12, 07, 1898. https://www.mdpi.com/2073-4441/12/7/1898.

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Conference Abstract

2. **Myo Lin, Nay** and Rutten, Martine (2017): Estimation of reservoir inflow in data scarce region by using Sacramento rainfall runoff model - A case study for Sittaung River Basin, Myanmar. EGU 2017-15891. https://presentations.copernicus.org/EGU2017-15891_presentation.pdf.

1. **Myo Lin, Nay**, Rutten, Martine and Giesen, Nick Van De (2016): Flood mitigation through optimal control of a network of multi-purpose reservoirs by using Model Predictive Control. In EGU General Assembly Conference Abstracts (pp. EPSC2016-5976). https://ui.adsabs.harvard.edu/abs/2016EGUGA..18.5976M/abstract.

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