STOCHASTIC DYNAMIC PROGRAMMING (SDP) AND SAMPLE STOCHASTIC DYNAMIC PROGRAMMING (SSDP) FOR OPTIMIZATION OF KOREAN HYDROPOWER PLANT

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ABSTRACT

As society is increasingly aware of the ecological value of water. As a result, sustainable eco-friendly hydropower reservoir operation is a priority to preserve downstream biodiversity while minimizing the impact on energy production levels. This study develops Stochastic Dynamic Programming (SDP) and Sample Stochastic Dynamic Programming (SSDP) optimization models to address minimum environmental flow constraints on hydropower operations levels and storage targets while reflecting the uncertainty in future inflow forecasts. A case study of the Bosunggang Hydropower system in Korea compares the performance of historical operations with decisions generated by SDP and SSDP models with different hydrologic state variables, state variable discretization, and system turbine capacities. A watershed model, SSARR, was successfully employed to obtain a daily soil moisture series representing the watershed's wetness. Importantly, simply adopting sophisticated optimization models without careful consideration of system characteristics such as basin hydrology and system objective does not guarantee better optimized system performance.

BIOGRAPHICAL SKETCH

Kwang-Bae Choi was born on April 5, 1982, in South Korea. He attended Dankook University in South Korea 2001, where he was awarded the Bachelor of Engineering in Civil and Environmental Engineering. Soon after obtaining his diploma, he started his career at an engineering consultant company in South Korea focusing on planning and designing water resources infrastructures including hydropower plants both in Korea and internationally. Since 2012, he has worked with a Korean governmental energy company, Korea Hydro and Nuclear Power (KHNP), where he worked in the hydropower business sector.

In 2016, he enrolled in Cornell University's graduate program at the School of Civil and Environmental Engineering, working with Professor Jery R. Stedinger and Dr. Rebecca Schneider. While at Cornell, his research focused on hydropower optimization subject to ecological constraints. His career goal is to pursue sustainable development for future generations.

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CHAPTER 1 INTRODUCTION

1.1 Motivation

Dams have been built throughout the world at a rate of about two dams per day for various purposes since 1970 (World Commission on Dams, 2000). Among the different types of energy sources, the distinct advantage of hydropower plants is that they generate eco-friendly electricity at a low cost. For example, in comparison to coal power plants, hydropower plants do not emit any CO_2, which is major contributor to global warming. Benefits of hydropower, particularly the value of hydropower generation, are achieved by the flow of water through the turbines; therefore, the amount of water present in a reservoir determines the potential value of future hydropower generation. Given these benefits, hydropower accounted for about 19% of the world's total electricity generation in the mid-1990s with an additional 3.6% of promising future growth rate per year between 1990 and 2020 (Lehner et al. 2005; Madani and Lund 2009). However, to make use of potential water energy efficiently, water needs to be stored in reservoirs, and that can lead to various impacts to the downstream ecosystems.

Such a conflict between ecological sustainability and economic benefits is common in hydropower operation. As people are increasingly understanding the importance of ecological sustainability, they recognize the need to integrate both ecological sustainability and economic benefits in managing hydropower plants. Currently, one of the simplest and most accepted methods to achieve the above goal is to establish a minimum release rate so water always flows in the river. This is called the minimum environmental flow. Minimum releases play a vital role in maintaining a balance between ecological sustainability and economic benefits. They have been recognized as a critical aspect in planning new dams and re-licensing existing dams (Renöfält et al. 2010).

However, from an economics' perspective, the aforementioned method could reduce the likelihood of maximizing profits from hydropower generation. Due to the hydropower agency's obligation to follow environmental flows regulations, a certain amount of the water has to be spilled into the downstream without generating power. It conflicts with the ultimate objective of operating hydropower plant for maximum output and diminishes the flexibility of reservoir operation. As a result, hydropower plant agencies have worked to identify ways to more efficiently use the water flows resulting from the introduction of the environmental flow requirement into system. In fact, this issue has been faced by most of the hydropower agencies globally. The Korean government has been establishing legal environmental flow requirements since 1990 to maintain water quality and preserve downstream ecosystems along the whole river.

This research will focus on Bosunggang hydropower plant in Bosunggang River, Cheon-nam province in South Korea, where new legal environmental flow requirements have recently (in October 2015) been imposed to protect the downstream ecosystem by the Korean government. Before the regulation, downstream spill from Bosunggang reservoir has rarely occurred except during the flooding season since the hydropower plant was built in 1936. However, about 6 percent of the annual average inflow now has to be released, without power generation, to meet the new environmental flow regulation. This translates into there being no turbines in the direction toward downstream. Thus, the hydropower agency is anticipating, with some concerns, a long-term reduction in hydropower generation from the Bosunggang hydropower system. This research aims to investigate non-structural alternatives to keep the energy production equal to its pre-regulation level or to potentially gain more power under the legal minimum environmental flows requirement.

1.2 Objective

As there has been an increasing social demand for environmental protection in river systems, legal requirements are now in place to preserve river ecosystems in many countries. The viable approach to account for ecological values in a hydropower system is to include environmental constraints into the mathematical optimization methods used to determine hydropower operations. This approach has long been favored by related decision makers because of its capability of answering the following question: what is the best decision regarding flow releases given certain objectives and constraints. It is true that before the use of the mathematical approach for reservoir operations became prevalent, most operators relied on simple predefined rules or simple simulation models to plan operations (Bessler et al. 2003; Jager and Smith 2008). More recently, mathematically-driven optimization modelling methods have started taking center stage to establish a desirable release schedule. These models are then combined with simulations to validate the model. Optimization models can be applied in small river systems to incorporate ecological values as objectives. In the near future, there will be further opportunities in evolving those models for use in other water resource systems (Jager and Smith 2008).

Jager and Smith (2008) categorized the reservoir operation as a step-wise decision tree to suggest a desirable reservoir optimization approach for securing healthy river ecosystems (Figure 1-1).

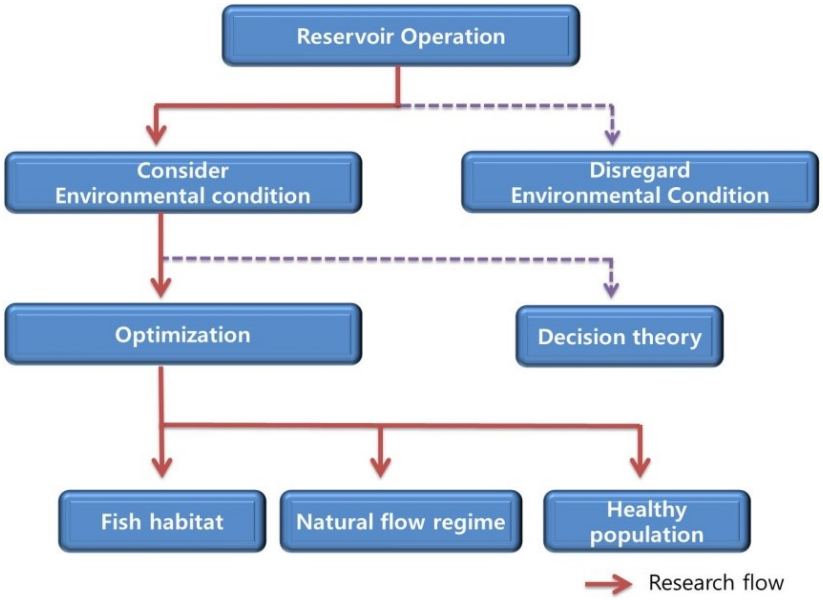


Figure 1-1 Classification of reservoir operation problems with environmental consideration (Jager and Smith 2008)

A review of the literature indicated that more than half of reservoir operation studies (e.g., Babel et al. 2012) deal with the environmental aspect as a constraint component in reservoir optimization. These strongly support the approach of this study in terms of research objectives as well as motivation.

Among various optimization models which have been used, Dynamic Programming (DP) has been shown to be a desirable technique for hydropower system analysis because of its capability of implementing a successive decision at each time stage with a nonlinear objective, if needed. DP when formulated as an SDP algorithm is capable of taking into account uncertainty reasonably well. Thus, this thesis will attempt to go further by focusing on stochastic dynamic programming (SDP) and sample stochastic

dynamic programming (SSDP) using the relevant case study of the Korean hydropower system.

Although these methods have integrated different types of hydrologic state variables under different time steps, such modification has never been applied to the Korean reservoir systems with daily-based optimization (e.g., Kim et al. 2007; Eum and Park 2010; Kim et al. 2011). Instead, other researchers have been using SSDP with ESP (scenarios based) to optimize the multipurpose dams in Korea. They have deliberately left using physical hydrologic state variable (e.g., snow and soil moisture) into optimization as a future effort. This indicates that extensive reservoir optimization has not yet been truly evaluated with diverse hydrologic factors, and especially for a small reservoir in Korea. Additionally, it is possible that more reasonable models can be built by considering additional system states regarding hydrologic characteristic (e.g., inflows persistence) in the hydropower plant system. Also, the short-term decision time step in hydropower operation is generally preferred because of its flexibility in dealing with sudden inflows and follow up market price instantly.

This thesis first aims to explore SDP optimization by integrating a hydrologic state variable, such as soil moisture using a short-term time step. The performance of the created models will be compared with historical operation records under various system configurations. The significant results from this work will provide: (1) a better understanding on how tradeoffs between hydropower production and legal environmental flows can be managed in the long run by reservoir optimization methods and (2) if SDP and SSDP optimization can improve the power production of present hydropower operations under the new regulation imposed by law, i.e. legal minimum environmental flow.

CHAPTER 2 BACKGROUND AND LITERATURE REVIEW

2.1 Introduction

Two main different topics are summarized herein as a literature review. First, the overall concept of minimum environmental flow will be described with relevant cases aiming to assess the effect of river regulation on downstream ecosystems. The second subsection describes the several optimization models used for hydropower systems in terms of each approach's methodology as well as its applicability to this study.

2.2 Environmental Flow in Hydropower System

Hydropower plant (HPP) has long been regarded as a promising energy resource because of its efficient cost, environmentally friendly generation and flexibility. First, the operation cost for hydropower is cheaper than for fossil fuel steam plant ($5/MWh vs $20/MWh) and gas turbines peaking units ($5/MWh vs $28/MWh) (Harpman 1999; Olivares 2004). Second, demand for renewable electricity sources, such as hydropower over fossil fuel, to help mitigate greenhouse gas emissions is increasing (Kosnik 2008). Finally, hydropower is a reliable energy source for flexibly meeting peak demand in that it can instantly respond to rapid changes in energy fluctuations within seconds. For these reasons, presently, the hydropower accounts for about 6.2% of total net electricity generation and nearly half (48%) of all renewable energy in U.S. (Hydropower vision report, DOE, 2015). Its popularity has been gradually increasing since society started perceiving impacts of CO_2 emissions derived from traditional energy resources such as fossil fuels (Renöfält et al. 2010). Generally, there are two types of hydropower plant: one incorporates the use of a dam, which necessarily requires the additional reservoir to store potential energy. the other types are called "run of river", which generates electricity by directly harnessing flowing river water – it has high potential without any

impounded storage. However, the latter type has limitations due to topography constraints to secure high effective head for stable power generation. Therefore, most hydropower agencies have commonly chosen the dam type which impounds water in the reservoir. However, there are potential impacts of building artificial reservoirs with regard to water temperature, sediment transport, floodplain vegetation communities, downstream estuaries and water quality (Williams and Wolman 1984; Vörösmarty et al. 2003; Todd et al. 2005; Richter and Thomas 2007). Among all the potential impacts, natural alteration of water flow regimes is perceived as a critical factor (Poff et al. 1997; Olivares 2004; Richter and Thomas 2007). Artificial reservoirs as well as its operations could change the volume, timing, frequency, and duration of water flows that can have spatial and temporal impacts to the downstream ecosystem (Resh et al. 1988; Poff et al. 1997; Richter and Thomas 2007). A comparison of the flow regimes in the Roanoke River in North Carolina with and without the dam presence (Figure 2.1; (Richter and Thomas 2007), demonstrates the greater peaks in flow under natural conditions.

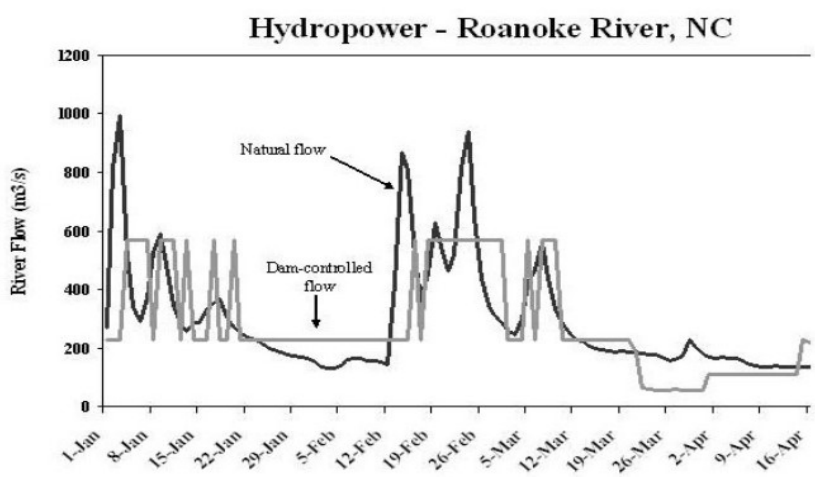


Figure 2-1 Operation of a series of dams for hydropower and flood control on the Roanoke River in North Carolina, U.S. (based on 1945 data*). from Figure 2, Ritchter and Thomas 2007*

For the regulated flows, river flows fluctuated over short intervals in early Jan between a minimum level of 200m^3/s and a maximum level of 600m^3/s with the aim of generating hydropower. From Mar 26 to April 16, the flows dropped lower than natural flows perhaps due to either reduced release or no release from the reservoir. This means that the dam regulates the flows by following a designated policy of reservoir operation for its power generation. In comparison to regulated flows, such static fluctuation pattern was not observed in natural rivers because no regulation existed before commencing the reservoir operations.

In contrast to base load energy sources, such as nuclear and coal-fired plants, which have some limitations in their ability to respond to fluctuating daily energy demands, hydropeaking operation enables the hydropower system to respond rapidly or even instantly. The time scales adopted in hydropower operation can be monthly, daily, and even hourly intervals (Olivares and Lund 2008); however, this designated interval of operation may interact with a diversity of environmental and ecological processes because the spatial and temporal scales of flows play a critical role to exist river system (Nelson et al. 2013; Shiau and Wu 2013). For example, some fish species have been shown to cue their spawning or egg hatching to rapid increases in flow velocity or to seasonal, spring-time rises in water level and flow. However, in the absence of a theoretical foundation to precisely and quantitatively evaluate the short time fluctuation of flow effects on the ecosystem, the problem of determining hydropower operations still remains complicated (Olivares 2008; Lee et al. 2013). In the real-world system, setting minimum environmental flows from reservoir to downstream has been the typical way to at least secure the downstream ecosystem against the most drastic impacts of total river dry-outs. In the next section, 2.2.1, the fundamental concept of minimum environmental flow and method of defining it will be introduced, and then this will be incorporated into reservoir optimization for the case study in chapter 3.

2.2.1 Concept of Environmental Flow

As indicated throughout the literature (e.g., Poff et al. 1997; Arthington. et al. 2006; Richter and Thomas 2007; Olivares 2008), the flow regime of a river system plays an important role in maintaining downstream habitats. However, there are no explicit standards in identifying the optimal flow regime that should be maintained against hydrologic alteration, and it has been an active research area (Rheinheimer 2011). At present, as a feasible alternative, the theory of minimum environmental flow is practically adopted in real hydropower systems as a strategy to protect downstream ecosystems. According to Moore (2004), the term of the environmental flow was firstly introduced in 1940's in the western United States when citizens began recognizing diminished number of fish species caused by loss of flow in river. In 1970's, environmental flow was called minimum flow or instream flow which represents the minimum amount of water needed to protect fishery species. This amount of water should flow continuously to maintain the conditions of eco-systems downstream of a reservoir. That was the primary definition of environmental flows in the U.S. and England (Kang et al. 2000). Since the 1970's, researchers started to recognize that a single minimum flow requirement was not enough to characterize the complex relationships between biological, social systems, and integrated river management. The riverine species needed to be evaluated with advanced environmental flow assessments in order to incorporate the full range of riverine species, processes and services (Bunn and Arthington 2002; Arthington. et al. 2006) .

After this time, more scientific and specific methodologies for establishing environmental flow began to emerge, such as the instream flow incremental methodology (IFIM) invented by Bovee (1978) in a US Fish and Wildlife Service Biological Services Program.

Clarify Terminology of Environmental Flows

Environmental flows have been referred to with a variety of terms such as instream flow, minimum flow and instream flow requirement, across the different research fields. However, there is a clear difference between these types of flow depending on their purpose. Moore (2004) pointed out the lack of uniform agreement for a definition of environmental flows in the literature (Table 2-1).

Dyson, Bergkamp and Scanlon (2003) in the IUCN guide on environmental flows define the concept as the water regime provided within a river, wetland or coastal zone to maintain ecosystems and their benefits where there are competing water uses and where flows are regulated.
The 4th International Eco-Hydraulics Symposium defined environmental flows as the water that is left in a river system, or released into it, to manage the health of the channel, banks, wetland, floodplains or estuary.
Arthington and Pusey (2003) define the objective of environmental flows as maintaining or partially restoring important characteristics of the natural flow regime (ie. the quantity, frequency, timing and duration of flow events, rates of change and predictability/variability) required to maintain or restore the biophysical components and ecological processes of in-stream and groundwater systems, floodplains and downstream receiving waters.
Tharme (2003) defines an environmental flow assessment (EFA) as an assessment of how much of the original flow regime of a river should continue to flow down it and onto its floodplains in order to maintain specified, valued features of the ecosystem.
IWMI (2004) defines environmental flows as the provision of water for freshwater dependent ecosystems to maintain their integrity, productivity, services and benefits in cases when such ecosystems are subject to flow regulation and competition from multiple water users.
Hirji and Panella (2003) define an environmental flow as an allocation of water with a prescribed distribution in space and time that is deliberately left in a river, or released into it to manage river health and the integrity of ecosystems sustained by the river flows.
Brown and King (2003) state that environmental flows is a comprehensive term that encompasses all components of the river, is dynamic over time, takes cognizance of the need for natural flow variability, and addresses social and economic issues as well as biophysical ones.

Table 2-1 Definition of environmental flow in related research, Moore (p.22, 2004)

More recent definitions of environmental flow are closely related to its role in protecting the ecosystem. Several papers have also expanded the scope of the definition of environmental flow, which was described as the quantity, timing and quality of water flows, and these elements are also vital to human livelihoods and resilience of the

aquatic ecosystems (Hirji and Davis 2009; Nyatsanza et al. 2015). In Babel et al. (2012), "environmental flow is regarded as a minimum safe guard for an aquatic ecosystem". This is thought to be the most appropriate term or explanation among others in the context of environmental protection for hydropower systems because other terms were heavily focused on flow quantity alone which might be considered a myopic approach to explain an ecosystem's complexity. As such, the term of environmental flow in this study will follow the definition used in Babel et al. (2012).

Environmental Flows Prescription

There are many approaches to calculate the amount of water necessary for environment flows. However, questions remain on selecting the appropriate method to satisfy quality, quantity, and the timing of reservoir operation in rivers (Renöfält et al. 2010; Ritcher et al. 2012). Several methods have been used to prescribe environmental flow requirements. These range from calculating a simple percentage of mean annual flow to conducting multi-year studies using expert scientific panels (Arthington et al. 2006). The most common way to organize these diverse methods is to divide them into three categories: historic flow methods, hydraulic rating methods, and habitat rating methods (Jowett 1997; Moore 2004; Arthington et al. 2006). Jowett (1997) explained and compared these three different types of methods to prescribe flow requirement. First, historic flow methods adopt an empirical method approach with the use of the flow duration curve and calculation of a certain percentage of the mean flow. Second, the hydraulic rating method entails analytical calculations to obtain a number of parameters (e.g., width, depth and velocity) of the hydraulic geometry in river channels. Lastly, habitat simulation methods, which includes the most frequently used method, involves a physical habitat simulation component (e.g. PHABSIM created by Milhous et al. 1989). PHABSIM determines the optimal condition for suitable fishery habitat by finding the relationship between weighted usable area (WUA) and hydraulic condition

in the stream (e.g., depth and velocity) (Olivares, 2008). Both habitat and hydraulic methods are similar in that they are based on employing hydraulic condition as a standard; however, they have different biological requirements for specific aquatic species. Each of the methods in the three categories has different advantages and disadvantages (Table 2-2).

Categories	Methods	Advantages	Disadvantages
Historic Flow Methods	- Tennant method - Hoppe method - Flow Duration Curve Method - Constant Yield Method	- It can represent variability of flow very well	- Hard to consider hydraulic variables and biological response
Hydraulic Rating Methods	- Habitat-Discharge Method - Simplified Staff-gage Analysis - R-2 Cross Method (US Forest Service) - WSP Hydraulic Simulation - Idaho Method - TexasWater Development Board Method	- It can interpret the river channel by applying diverse hydraulic variables (e.g., wetted perimeters) into habitat condition	- Need much data on hydrology and hydraulic dependence on magnitude of flow - Requires the procedure to depict directly the results from analysis with flow assessment
Habitat Rating Methods	- Usable Width Method - Weighted Usable Width Method - Preferred Area Method - Instream Flow Incremental Methodology (IFIM), PHABSIM. - Habitat-based quasi-population models - Dynamic model, SALMOD	- It can simultaneously interpret variability of fish habitat in terms of time and spatial condition - It can consider multiple habitat types and fish life-stages - It is suited to trade-offs situations	- Need various, specific information on ecological fish requirements - Calibration relies heavily on long-term and intensive monitoring efforts - Need solid knowledge of the stream and clear management objective (Jowett 1997).

Table 2-2 Summary of methods for prescribing minimum environmental flows with pros and cons of each method

Among habitat methods, the Instream Flow Incremental Methodology (IFIM), created by the U.S. Fish and Wildlife Service, has been the most frequently used method throughout the world. It has the advantages of flexibility and propriety of application tin trade-off situations so this method can be used in determining appropriate flow rules for river management (Kang et al. 2000; Moore 2004; Olivares 2008; Renöfält et al. 2010; Lee et al. 2013). However, IFIM also has disadvantages in that it cannot describe a temporal dimension and is not suitable for severe hydrologic and habitat events as well as short-term flow fluctuations (Hunter 1992; Hickey and Diaz, 1999; Olivares 2008). Therefore, more recently, habitat-based quasi-population models have emerged, followed by dynamic models, e.g. SALMOD, which is more refined with the ability of interpreting multiple habitat types and fish life stages (Harpman et al. 1993; Cardwell et al. 1996; Olivares 2008).

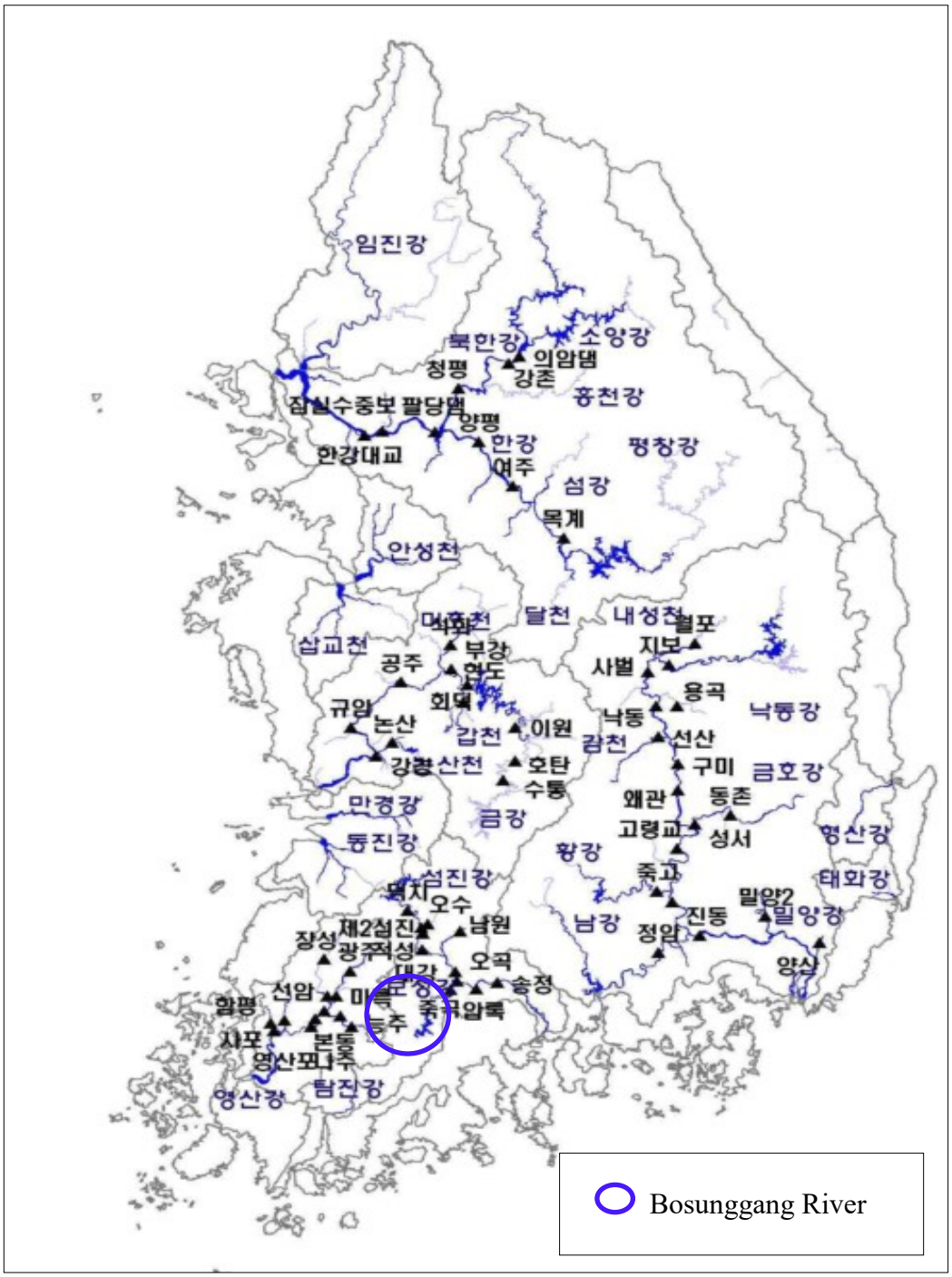
Environmental Flow Policy

Such environmental flows are usually specified as a regulation by public agencies, such as government or regulatory authorities. The hydropower system in the U.S. requires license and permit renewal every 30-50 years, which are obtained from the Federal Energy Regulatory Commission (FERC) under the Federal Power Act of 1920 and in accordance with the Electric Consumers Protection Act, Endangered Species Act, and National Environmental Policy Act (Kuby et al. 2005). The major environmental regulations now controlling hydropower relicensing specifies two components: (1) maintenance of minimum environmental flows throughout the year, and (2) including a gradual ramping rate in releases, both increases and decreases, to the downstream. This latter requirement allows more time for aquatic creatures to leave or find refugia before the maximum flow rates impact them. Of these two requirements, the minimum instream flow has become a critical aspect to continue operating facilities. Thus, proper methods for prescribing minimum environmental flow could be an

important issue among stakeholders as well as the hydropower owner (Rheinheimer 2011).

Compared to the U.S., the energy market in Korea has been managed by a central utility planner, with the objective of securing electricity demand at minimum costs. Thus, licenses to build and operate dams are given to public corporations that are owned by the central government. In the 1980s, most dams in Korea were exclusively used for water supply and hydropower production to secure a stable water supply for daily living and agriculture, and meet the electricity demand for industrial development. Operation policy was solely determined to take account of the above main purposes of dam. However, due to a significant increase in awareness of environmental and ecological protection in recent years, the operation policy of Korean reservoirs has changed to start considering downstream releases. For example, the government has established a law to determine the environmental flow along the rivers; certain amount of water must be spilled from the reservoir into downstream to maintain the ecosystem.

Although in 2007 the government announced the requirement of a legal environmental minimum flow, in practice, the practical and specific application for an environmental flow policy has rarely been developed. The main limitation is that it was too difficult to identify the required minimum flows for conserving certain creatures among the diverse species living in the rivers. The official definition of environment flow specified by river law in 2007 was "the necessary minimum flow to maintain normal functions and condition of the river." Additionally, in the special case of water deficit, the law allows for limiting permission or minimizing the water usage by reservoir operation agencies. In order to manage the environmental flow consistently, the government created an integrated water resources long-term plan to forecast future water demand, which is re-defined every decade. 60 locations throughout the country were identified in 2007 as sites for specifying legal environmental flows (Figure 2-2).



Bosunggang River

Figure 2-2 Location of rivers established legal environmental flow in 2007

Similar to Korea, Sweden is also a country in which there is no re-licensing procedure, but federal regulations require that operating conditions are supposed to be assessed regularly (Rheinheimer 2011). Several regulations have been developed and applied in hydropower planning to mitigate possible environmental effects. For example, the well-known mitigation specified by regulation in Switzerland is called "green hydro assessment procedure", which is a strong ecological assessment procedure for evaluating environmentally compatible hydropower production by certification procedures (Truffer et al. 2001; Bratrich et al. 2004; Renöfält et al. 2010). The basic goals of green hydro certification pertaining to hydrological management have been divided among five different fields including connectivity of river system, solid materials regime and morphology, landscape features and biotopes, biological communities (Table 2-3; (Bratrich et al. 2004; Renöfält et al. 2010)).

Hydrologic requirements
1) Instream flow regulation - Instream flow must follow seasonal changes and the variability of natural discharge patterns.
2) Hydropeaking regulations - For migration of aquatic organisms as well as alleviation of temperature effect, hydropeaking operations need to be slowed down.
3) Reservoir management - Flushing of sediments to the downstream region below the reservoir must take place during high discharge.
4) Bedload management - The minimum flow regimes should be met for sediment transport, bank erosion and deposition as natural condition.
5) Design of power plant structure - The design should include control systems which prevent sudden high-volume releases and technical measures to meet minimum environmental flow regimes at any time.

Table 2-3 Hydrological requirements in the 'GreenHydro' concept, developed by the Swiss Federal Institute for Environmental Science and Technology (EAWAG) (from Table 1, Bratrich et al. 2004, page 872)

For further understanding on environmental regulation, Rheinheimer (2011) suggested two aspects that need to be considered and understood in quantifying environmental effects in hydropower systems. First, verification of the relationship between hydropower systems and ecosystem in relation to river regulations. Second, examination whether existing hydropower system policies could be modified to enhance environmental performance. The majority of early environmental flow studies had typically been crucial consideration for reservoir operation agencies and stakeholders in constructing new dams and in re-licensing existing dams. However, environmental flow studies have now been extensively adopted in other fields such as the river restoration community for integrated water resources management on water usage (Cha et al. 2009; Renöfält et al. 2010; Babel et al. 2012).

Some relevant studies have been carried out by coupling optimization or simulation methods with ecological information in order to define the required inflows that could best protect certain targeted species (Sale et al. 1982; Cardwell et al. 1996; Suen and Eheart 2006; Chen et al. 2015). Sale et al. 1982 was the first study to take into account the weighted usable area (WUA) into reservoir optimization for maximizing success of multiple fish species and life stages. Moog (1993) investigated the impacts of daily peak hydropower on aquatic fauna, and suggested management strategies to minimize environmental impacts. In addition, Stalnaker et al. (1996) emphasized not only spatial features of habitat but also temporal dimensions of instream flows and their effect on fish habitat in riverine environments. Babel et al. (2012) used the simulation model to deal with trade-offs between hydropower production and environmental flow requirement, and demonstrated that alteration of the natural flow regime in the river could be alleviated by making suitable operating policy changes in the system without affecting power production.

Recently, mathematical optimization methods (e.g., linear programming (LP), Dynamic programming (DP)) were introduced to deal with trade-offs between economic benefits and environmental protection. In addition, Olivares (2008) employed Sampling Stochastic Dynamic Programming (SSDP) to perform a spatial assessment of hydrologic alterations within a river network to identify the effectiveness of selective withdrawals from reservoir, and found that it was significantly related to reservoir temperatures.

As an alternative to the emerging focus on minimum environmental flow, which potentially limits peak power operation in a hydropower system, Pérez-Díaz and Wilhelmi (2010) used a revenue-driven daily optimization model with mixed integer linear programming. This study observed diminishing marginal economic costs of decreased ramping rate restrictions. Jager and Smith (2008) conducted a literature review on sustainable reservoir operation in hydropower systems with a focus on hydropower revenue, water quality, and fish populations, and found that many studies (14 of 29) addressed the environmental flows as a constraint equal to minimum flow releases in reservoir optimization. Rheinheimer (2011) used linear programming (LP), with the consideration of both minimum environmental flows and weekly down ramp rates, to develop a multi-reservoir optimization model that evaluated possible climate change effects by setting different air temperatures. These could become critical components in defining trade-offs related to generating hydropower profits. Shiau and Wu (2013) optimized environmental flow for a multipurpose reservoir system in the development of an operation strategy under sub-daily flow regime in Taiwan. They demonstrated that incorporating environmental flows as an objective does not necessarily degrade the overall reservoir performance due to the offsetting positive effects on flood control. This would, in turn, compensate for the adverse effects on domestic water supply and hydropower generation.

Although most previous studies merely focused on the physical scheme of environmental flow, several studies extended their focus to the economic aspects of hydropower operations. Harpman (1999) analyzed the economic costs of environmental flow on hydropower releases in Glen Canyon Dam and estimated that about 8.8% of hydropower reduction in the short-run could be expected. Kotchen et al. (2006) assessed the economic benefits to society and costs to power producer resulting from dam re-operations for increased environmental flows, and concluded that the benefits significantly exceeded the costs by allocating more water to the downstream. Most recent study, Olivares et al. (2015) proposed identification of pareto-efficient environmental constraints by considering trade-offs between cost and the short-term operation effectiveness with regard to sub-daily hydrologic alteration.

Domestic researches in Korea for environmental flow mainly focus on two parts: water quality and ecological flow required for certain organisms in a targeted location. The 1-dimension model was successfully applied for a Korean reservoir system to prescribe amount of minimum environmental flow by considering fish habitat in Geum River as a first domestic case (Woo et al. 1998). After that, in order to overcome limitations of the 1-D model, PHABSIM, more integrated methods were invented, such as River-2D, which resulted in better performance (Roh et al. 2012). Furthermore, Ko et al. (2009) implemented ecological-hydrological analysis to demonstrate flow regime changes derived from Yong-dam multipurpose dam and Dae-cheong multipurpose dam by coupling with K-modsim, which is a watershed model and RAP (Cooperative Research Centre, Australia, Marsh, 2004) which is an eco-hydrological assessment model. Cha et al. (2009) discussed the effect of upstream dam discharge on water quality improvement in the Yeong-san River in Korea with desirable suggestions including water quality management using one dimensional riverine water quality model, QUAL2E model.

Trade-offs in Hydropower System

Thus far, several methodologies and relevant studies for defining minimum environmental flows have been discussed. Although there has been a wide range of trials to equally address both economic benefits and environmental sustainability, it is still hard to achieve a balance between these two major goals (Figure 2-3)

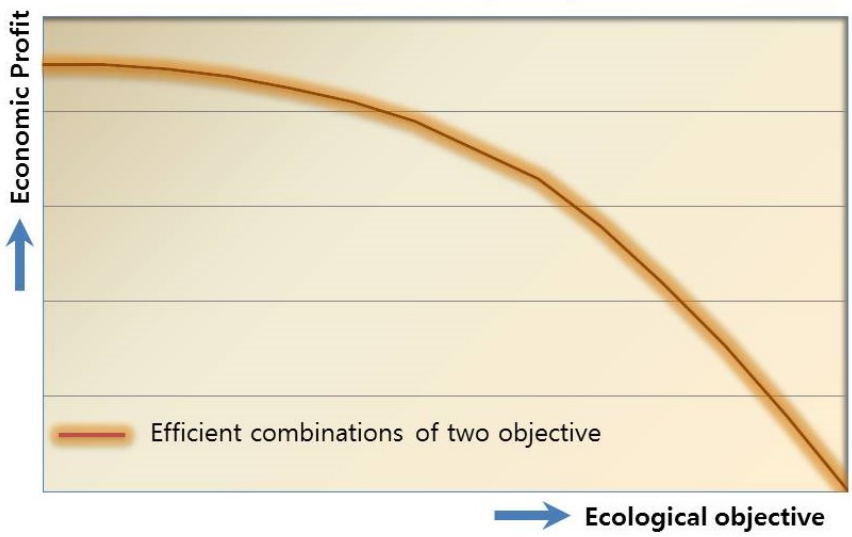


Figure 2-3 Trade-off between hydropower production and minimum environmental flow

There are losses and gains when the aim of increasing revenue by maximizing hydropower production is balanced by addressing the controls on flow needed for meeting the minimum environmental flows, and vice versa. The compromise solution involves accepting trade-offs between both goals. Acknowledging the trade-offs became a vital component in planning and managing of water resources, and allowed for the acceptance of a compromise solution to hydropower operations. To examine the various trade-offs, there have been a wide range of studies which couple an optimization approach with ecological components. For example, in recent studies on environmental issues in hydropower system, Ferreira and Teegavarapu (2012) coupled trade-offs between water quality and hydropower production by implementing mixed integer nonlinear programming with a genetic algorithm model (GA).

Yang et al. (2012) performed optimization to minimize changes in the natural flow regime downstream of the Danjiangkou reservoir, China. In their compromise solution, the power output was unavoidably abated and decreased in order to meet the environmental objective because they were non-commensurable and could not be integrated into a single objective (Ferreira and Teegavarapu 2012). Kuby et al. (2005) used multi-objective optimization models to examine trade-offs between salmonid migration and hydropower production. As such, the theory of trade-offs has been frequently realized in hydropower systems to attain both ecological and economic gain. Hence, understanding of this concept should be considered when setting up new hydropower operation policy to balance between generating profit from hydropower and minimizing environmental impacts.

Decrease of Economic Profits due to Environmental Flow

Although prescribing environmental flow in hydropower system can be potentially advantageous for the ecosystem, it adversely decreases hydropower production, thus reducing anticipated profits. For example, in the case study for Zambezi basin in Southern Africa studied by Nyatsanza et al. (2015), the loss of hydropower production was estimated between 3 and 33% as a result of restoring natural flows in the lower Zambezi. Similarly, Harpman (1999) estimated that the short-term economic loss of the Glen Canyon Dam in Colorado River caused by environmental constraints was 8.8%. Although it seems to be a small relative proportion lost economically, the absolute monetary loss is not trivial as the value of water in one cubic meter per second is worth 41,000 USD per year (Olivares 2008). Likewise, environmental flow regulation poses a critical challenge for hydropower producers because they must simultaneously adapt flexibly to the fluctuating market price. This may eventually bring additional efforts to make up the reduced profits derived from strict reservoir operation associate with minimum environmental flow requirement.

2.2.2 Summary

Overall, the previous chapters have examined the environmental flows theory in context of hydropower system and discussed its application in relevant literature. As awareness of ecological value has been increasing worldwide, traditional objective of hydropower operation to make economic benefits from electricity generation is unavoidably facing transition in order to harmonize with the associated aquatic ecosystem. However, this is proving to be fairly challenging work in hydropower operation due to the inherent difficulties of quantifying the economic value of environmental components (e.g., sanctuary and biotope) in comparison to other tangible economic benefits (e.g., electricity profits and water supply) (Truffer et al. 2001).

Even though innovative methods to maintain natural flow regime have been applied in the real-world to mitigate the impacts on the alteration of flow regime, there is no simple or most desirable solution to satisfy the optimal flows conditions for both ecosystem protection and reservoir operations. This is because of the complexity of quantifying natural flow regime and the absence of certain standards for acceptable limitation of disturbance in rivers with respect to the effects of flow regulation on ecosystems (Olivares 2008; Jager and Smith 2008). Although the traditional method, setting minimum release from the reservoir as environmental constraints, can be somewhat narrow and simple approach, it can act as serve as a viable proxy for quantifying environmental values under non-static river conditions. Many studies have successfully utilized this traditional method and observed positive results in balancing both environmental flows and economic objectives by adopting an optimization-based approach (Suen and Eheart 2006; Renöfält et al. 2010; Babel et al. 2012). It can be considered the closest approach to account for ecological requirements in hydropower operation.

In addition, in order to accomplish desirable hydropower operation under incomparable conflicts, it takes continuous engagement of multiple stakeholders and negotiations to reach consensus for the optimal usage of limited water resources between hydropower agency and government institution (Richter et al. 2006; Ritcher et al. 2012; Nyatsanza et al. 2015). It is true that many hydropower agencies and water managers have been committed to finding better solutions to maintain ecosystem sustainability. Both availability and sustainability of water resources can be reasonably achieved by the constant involvement of various stakeholders in water resource system (Loucks et al. 2005). Furthermore, responsibility for protecting ecosystems exists not only at the regional level but also worldwide since the 20th century. Lastly, although imposing minimum environmental flows to releases to downstream habitats can be a feasible approach to protect the ecosystem, it needs extensive efforts to minimize gap between the theory and specific local impacts to aquatic species diversity and whole ecosystem health.

In this section, the relationship between hydropower operation and social benefits was introduced, and discussed current controversies in trade-offs. In the next section, we will discuss hydropower optimization as a reasonable alternative to improve the hydropower operation benefits and resolve the environmental constraints.

2.3 Hydropower Optimization

In order to meet the increasing demand for water, a number of projects of hydropower plants have been carried out worldwide, and their first priority is of course achieving multi-objective benefits as originally intended. Unfortunately, the projects are rarely fully satisfied on efficiency of reservoir systems due both to a variety of unpredictable factors or uncertainties (e.g., future inflow, climate change, and variation in human population) and prosaic reservoir operation policy. These factors force

operators to make difficult decisions at each operation time step whether it be monthly, weekly or even daily. For instance, the reservoirs near the city usually have multiple objectives (e.g., water supply, hydropower, flood control and recreational activity) aiming to provide a stable water supply to people or industries and to protect people against floods while also meeting the imperative requirement that river flow regime should be maintained (2.2.1). Thus, any decisions about releasing flow or maintaining reservoir water level or meeting ecological demand for downstream ecosystems should be made with an effective and reasonable decision support system. As a feasible alternative, they can include an optimization algorithm, which can provide water resources modelling, scenario analyses, and optimization capabilities (Delipetrev 2016).

Many trials have been implemented with different approaches by various modelling optimization and simulation techniques. In this study, optimization method using a mathematical algorithm, will primarily focus on building an operating policy of hydropower reservoir given strict constraint in the system. Specifically, the constraint is the minimum environmental flow with the objective function, which is the expectation value to be maximized. A range of studies using the optimization method have been extensively carried out with diverse approaches depending on the different time horizons, objectives, and ways of accounting for uncertainties (Labadie 2004; Olivares 2008; Ahmad et al. 2014; Singh and Singal 2017). Fortunately, recent enhancements of computer performance have reduced the time needed for calculating complex mathematical optimization processes. As a result, various optimization algorithms have recently emerged and are continuously evolving (e.g., Artificial Bee Colony (ABC), Gravitational Search Algorithm (GSA). At this time, they have been practically applied into diverse fields of engineering (Ahmad et al. 2014).

Representative optimization techniques in the field of reservoir operation are extensively reviewed by various authors (e.g., Yakowitz 1982; Yeh 1985; Labadie 2004;

Olivares 2008; Ahmad et al. 2014; Singh and Singal 2017) and summarized in a classification scheme (Figure 2-4 Reservoir optimization classification, (Ahmad et al. 2014, page 3394, Fig. 1): Linear Programming (LP), Non-Linear Programming (NLP), Dynamic Programming (DP), Computational Intelligent (CI).

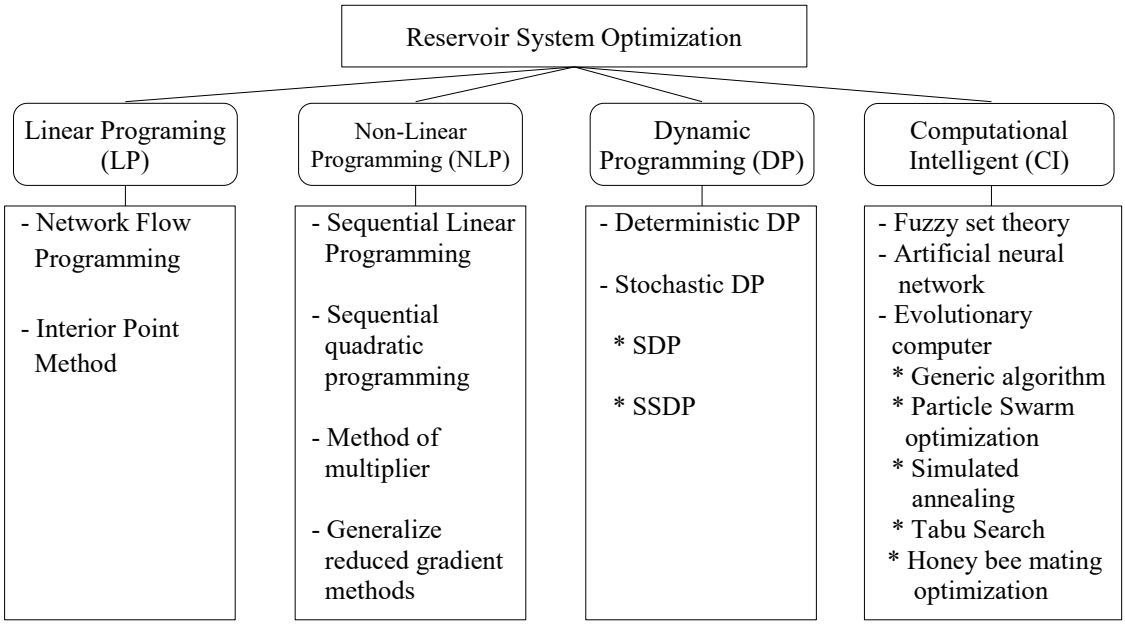


Figure 2-4 Reservoir optimization classification, (Ahmad et al. 2014, page 3394, Fig. 1)

LP has long been popularly accepted, not only by the field of reservoir optimization but also many other fields beyond engineering (e.g., business and finance) due to its advantage of building simple and flexible optimization models which can be applied into complex systems (Labadie 2004; Locuks et al. 2005). However, traditional LP cannot directly deal with non-linear problems that are a common feature of reservoir operations when hydropower generation is involved. These limitations require additional work, such as piecewise linearization approximations in order to transform non-linear functions into linear ones for solutions, and can result in computational burden (Loucks et al. 2005).

As an alternative to linear programming in reservoir optimization, Nonlinear Programming Model (NLP) such as Sequential Linear Programming (SLP), Sequential Quadratic programming (QLP) and the Generalized Reduced Gradient method (GRG) were successfully employed into reservoir optimization studies (e.g., Yeh et al. 1976; Murtagh and Saunders, 1982, 1987; Grygier and Stedinger 1985; Lall and Miller 1988; Tejada et al. 1990; Unver and Mays 1990; Oron and Rabinowiz 1991; Arnnold et al., 1994; Barros 2003). Among NLP methods, the SLP has turned out to outperform others in terms of its efficiency and accuracy to find an optimal solution (Grygier and Stedinger 1985; Hiew 1987; Peng and Bras 2000; Barros 2003; Labadie 2004).

However, several drawbacks of NLP were reported in the literatures. It needs more time and memory as procedures to build optimization problems mathematically are quite complicated (Yeh 1985; Singh 2012). In addition, there is no assurance that it will converge on a global solution unless the "algorithm is fully initialized close to a desirable solution" (Labadie 2004; Bazaraa et al. 2006). Lastly, the randomness commonly embedded in water resources system as a feature, such as inflows, is hardly taken into account (Yeh 1985; Kim et al. 2007).

Recently, the Computation Intelligence (CI) is becoming a promising method in reservoir optimization because of the its pronounced strength in identifying global optimal solutions with a reasonable computation time (Labadie 2004; Ahmad et al. 2014) and its ability to tackle the dimensionality problem in traditional optimization methods. In particular, as class of evolutionary algorithms, Genetic Algorithm (GA), is capable of heuristically handling nonlinear and multi-objective analysis with the additional advantage of directly coupling with other optimization models such as Artificial Neural Network (ANN) or simulation model (e.g., Oliveira and Loucks 1997; Labadie 2004; Reddy and Kumar 2006; Kim et al. 2007; Ferreira and Teegavarapu 2012).

Above all, DP-based optimizations including SDP, are an appropriate approach for successive decision processes in water resources systems given the time horizon because of several distinguished advantages. First, it can handle stochasticity in which variables such as inflows are all randomly occurring so that the uncertainty in the reservoir system can be reasonably taken into account. Second, it has the ability to represent feedback on optimal policy (Labadie 2004). Third, non-linearity in reservoir systems can be successfully handled by DP. Lastly, it can efficiently divide original problems with a large number of variables into a set of smaller optimization problems that can be solved recursively (Yeh 1985; Loucks et al. 2005). Among the optimization methods presented, DP as well as extended versions of DP such as SDP and SSDP will be mainly discussed in this study because DP has been more frequently used and practically applied in real-world reservoir optimization with the ability of dealing with uncertainty.

The basic elements of DP formulation consist of stage, decision variable, state variable, and stage return (Mays and Tung, 1992). First, stages are the points at which decisions are to be made and they correspond to the time steps of the optimization. Second, decision variables are recommended actions in each stage concerning the objective of the optimization. For instance, in reservoir optimization, final storage (S_{t+1}) or release (R_t) are ordinarily employed as the decision variable in each stage. Third, state variables describe the state or condition of the system in each stage. Storage and inflows are commonly used state variables in reservoir optimization. Lastly, stage return (B) is a scalar measure resulting from decision making in each stage. It can be expressed by quantified measurement such as monetary values. The principle of optimality of Bellman (1957) is the major concept of DP: regardless of decisions that were made in previous stages, DP finds the best option for maximizing stage return independently based on the state defined from the previous decision. The typical formulation of DP in

reservoir optimization is shown in (2-1) and represented schematically in Figure 2-5 (Kelman et al. 1990).

$$f_t(S_t) = \max_{R_t}(B_t(S_t, R_t, Q_t) + f_{t+1}(S_{t+1}) \tag{2-1}$$

$$\forall S_t, \text{ and } t \in \{1,2,\ldots,T\}$$

$$S_{t+1} = S_t + Q_t - R_t - e_t$$

Where,
$f_t(S_t)$ = *Value function in time t,*
$f_{t+1}(S_{t+1})$ = *Future value function in time t+1*

t = Stage, time step, T = Final time step in the model

B_t = *Benefit function at time t,* S_t = *Storage vector at time t*

S_{t+1} = *Storage vector at time t+1,* $R_t =$ *Release vector at time t*

Q_t = *Total inflow at time t,* e_t = *Evaporation loss*

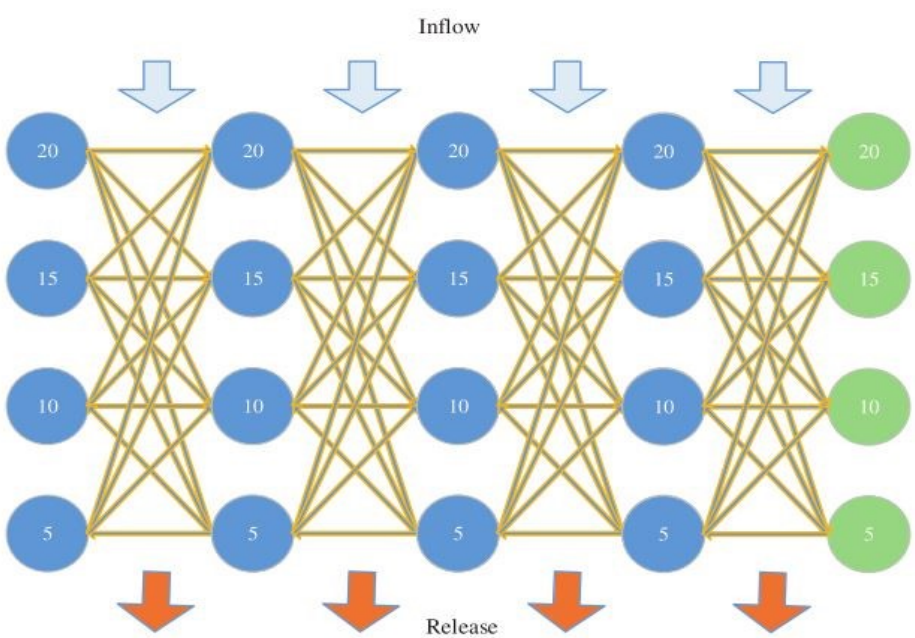


Figure 2-5 Scheme of DP in reservoir system, (Delipetrev 2016, Figure 2.2)

Figure 2-5 schematically illustrates of the multistage successive decision-making problem of DP algorithm from; Figure 2.2, pp.15). Specifically, the example of a DP algorithm consists of four-time steps in which each stage is transitioned through the yellow lines. The four circles in each column represent different storage volumes at each time t, first system state variable, S_t. The upper filled blue arrows indicate reservoir inflows, second system state variable Q_t. The yellow lines indicate state transitions from the preceding season to the following season at each system stage, t. The red filled arrows represent reservoir release, R_t, a decision variable. This value is chosen from all the possible alternatives that can maximize the sum of the current benefit B_t and the future benefit, $f_{t+1}(S_{t+1})$. $f_t(S_t)$ becomes a cumulative expected reward derived from applying the optimal release decision from time t to T. The backward recursive equation of DP, (2-1) above is then implemented from the end of the time horizon to the first stage step based on the mass balance equation until a steady state is reached; the optimal policy becomes constant at any stage, and then recursive computation is terminated (Loucks et al. 2005; Delipetrev 2016). Many reservoir optimizations were successfully carried out by using a DP (Yakowitz 1982; Wang and Adams 1986).

2.3.1 Stochastic Dynamic Programming (SDP)

The pre-determined inflow series adopted in DP has a major drawback in that it will not take place repeatedly in the subsequent horizon. For instance, in Figure 2-5, the inflows with blue arrows are not always certain constant vectors along the horizon, which means that inflows are uncertain with a stochastic characteristic. This randomness can result in lowering the possibility of achieving global optimality that can be derived from manifold possibilities of occurring inflows (Giles and Wunderlich 1981; Chen 2004). For this reason, Deterministic DP can be regarded as a simplistic and biased

algorithm in dealing with uncertainties in real world situations. Also, DDP overestimates system benefits and underestimates costs losses (Chen 2004).

Due to these limitations of deterministic DP, a more advanced and integrated reservoir operation technique was invented: SDP (Masse 1946; Little 1955). Its effectiveness at representing stochasticity in reservoir optimization has been demonstrated in many studies. Kim (1996) defined two major uncertainty sources in water resources systems. First, hydrologic uncertainty that takes place as a result of inherent inexplicable random hydrologic phenomenon. For example, one cannot precisely forecast future extreme rainfalls or drought. Second, information uncertainty that is caused by the lack of perfect information. For instance, historical data in analyzing reservoir optimization contains errors and inaccurate information. There are additional uncertainties associated with the economic context of the energy industry or with political aspects in water resources systems. For the sake of simplicity, this thesis will only focus on hydrologic uncertainty and this will be referred to as general uncertainty in this context. To summarize, the pronounced difference between DDP and SDP is the way of coping with reservoir inflows as to whether it considers the randomness of inflow, i.e. stochasticity under the unforeseeable natural hydrologic event. The hydrologic uncertainties in reservoir operation can be reasonably taken into account by SDP.

Masse (1946) was the first to apply the SDP to reservoir operations (Lamontagne 2015). Such a model can aid reservoir operators in making decisions confidently by suggesting optimal operation rules given the variable reservoir conditions (e.g., hydrology, seasonal weather and energy market) with respect to expected benefits resulting from its consecutive decisions. SDP has also been well-employed into many hydropower optimizations by capturing hydrological uncertainty using the reasonable probability approach.

There have been many other cases in successfully applying SDP for reservoir optimizations (Howard 1960; Arunkumar and Yeh 1973;Takeuchi and Moreau 1974; Turgeon 1981; Bras et al. 1983; Stedinger et al. 1984; Terry et al., 1986; Kelman et al. 1990; Karamouz and Vasiliadis 1992; Tejada-Guibert et al. 1995; Eum 2004; Kim 1996; Kim and Palmer 1997; Turgeon 2007; Côté et al. 2011; Desreumaux et al. 2014; Delipetrev 2016).

Although models of DDP and SDP have been frequently applied in the reservoir optimization, there is still a continuing gap between theoretical development and real-world application, which is the "curse of dimensionality" (Bellman 1961; Yeh 1985; Labadie 2004; Kim 2005; Lamontagne 2015). Several reasonable approaches for solving this issue will be introduced in a later chapter.

Background of SDP

No matter which optimization method is chosen, the objective in reservoir operation optimization is to maximize the expected benefits or to minimize the deviation from the target operation value over a planning period given the limited resources. For example, in water supply, performance may be expressed by either minimizing water deficit or maximizing annual hydropower profits. Additionally, in reservoir optimization, multiple objectives may concurrently exist with trade-offs. These trade-offs can be addressed by 1) defining one of the objectives as the major objective and others will be treated as constraints, or 2) each objective will be weighted differently based on its importance or priority. In this thesis, the primary objective is to maximize revenue of hydropower and will be the primary consideration, but with the constraint that a minimum environmental flow must be maintained.

In Equation (2-2), the return function (Z) is the performance measure of system used to define the optimal solution, which can yield maximum benefits for certain objectives by considering the state variables (Chen 2004). However, other objectives

can be identified by different return functions, which can also be called value functions. The random variable, reservoir inflows (Q_t), can be expressed by probability distributions that permit the computation of the expected present benefits (B_t) as well as future benefits ($\nu(S_{t+1})$) that is determined by release (R_t). These are chosen with respect to possible range (Q_t), and then the optimal decision can be made at each operational time step (t).

$$Z = [\sum_{t=1}^{T} B_t(S_t, R_t, Q_t) + \nu(S_{t+1})] \tag{2-2}$$

Based on the optimization objective, decision and state variables should be first defined with a time horizon, which can be broken into appropriate time steps such as monthly, weekly, or daily. The decision variable can be either final storage or release and are major factors for identifying the benefits derived from certain actions. In general, the decision variable is to determine the amount of water to be released through the turbine from the reservoir in this hydropower optimization study. This important variable accounts for the expected revenue in power generation over the planning horizon. On the other hand, the state variable (e.g., inflows and reservoir storage) represents the system condition at each stage with the relevant information. In particular, the state variable of inflow can be applied into SDP in a different way such as forecast variables or reservoir level depending on its features of representing system state in its derived time basis. The SDP equation has been continuously updated or transformed by different researchers, with the aim of enhancing optimization accuracy. The simplest SDP algorithm for reservoir optimization is to consider inflow uncertainty with probability distribution as in equation (2-3) (Tejada-Guibert et al. 1995; Faber and Stedinger 2001).

$$f_t(s_t) = \underset{q_t}{E}\left[\max_{u_t}\{B_t(s_t, u_t, q_t) + f_{t+1}(s_{t+1})\}\right] \tag{2-3}$$

$$\forall\, s(t), \text{ and } t \in \{1, 2, \ldots, T\}$$

One of the common approaches to SDP is to assume that the current period's inflow (q_t) is known. This assumption was introduced by Stedinger et al. (1984). This assumption is acceptable due to the fact that it is reasonly applicable for operators to adjust the release at the beginning of each time step when the current actual inflow is specified ahead of time. In reality, the above assumption is quite applicable with an additional advantage that it makes compututation simpler because a release adjustment associated with the target release is not needed (Stedinger et al. 1984; Faber and Stedinger 2001; Lamontagne 2015). With the similar procedure of computing DP, optimal release u^{opt} is determined by both state variables, s_{t} and $\mathrm{q_t}$ at each stage, and the unconditional probability is considered in the outer expectation, E.

Hydrologic State Variable

Equation (2-3) assumes that flows are independent so each expectation value is computed with simple unconditional probability of occuring inflows (Turgeon 2005b). However, on the basis of the fundamental characteristic of hydrology, high flows are ususally followed by high flows; similarly, low flows are flollowed by low flows. Such a predictable pattern is called streamflow persistence (Loucks et al. 2005). In fact, the shorter the time step of computation, the greater the corrleation or dependence that exists between succesive inflows. Therefore, the SDP algorithm has been modifed to account for hydrologic persistence by including additional hydrologic state variables so that it refines the existing algotithm as in Equation (2-4) (Tejada et al. 1995; Faber and Stedinger 2001; Turgeon 2005).

$$\mathrm{f_{t,}(s_{t,}q_t)} = \max_{\mathrm{u_t}} \left\{ \mathrm{B_t(s_t, u_t, q_t)} + \underset{(\mathrm{q_{t+1}|q_t})}{\mathrm{E}} [\mathrm{f_{t+1}(s_{t+1,}q_{t+1})}] \right\} \qquad (2\text{-}4)$$

$$\forall \mathrm{s_{t,}q_{t,}}, \mathit{and}\ t \in \{1,2,\dots,T\}$$

In the initial stage of incorporating the hydrologic state variable, the typical choices for such variables were either the previous period's streamflow or the current period's streamflow. These worked well with an order one Markov process where the current inflow is solely conditioned by prior inflow as below (Faber and Stedinger 2001; Loucks 2005; Turgeon 2005).

However, typically, correlation between subsequent inflows is stronger in a short time step, such as on a daily basis, than for a longer time step such as monthly. In addition, the correlation is beyond lag 1, and is expected to involve a greater number of past inflows for estimating current inflows (Turgeon 2005). Therefore, higher order autoregressive models were also used by many researchers to cope with the above issue such as ARMA and PARMA (Box and Jenkins 1970; Born 1988; Chen 2004; Turgeon 2005; Desreumaux et al. 2014).

In Turgeon et al. (2005, 2007), SDP was employed in order to solve the daily-based problem with AR and ARMA models using a single hydrologic variable to consider the persistence of serially correlated inflow. Another way of recognizing inflow persistence is via a seasonal forecast, which can provide more diverse hydrologic information than a simple Markov chain. Stedinger et al. (1984) used the best forecast of the current period's inflow as a hydrologic state variable for the Aswan Dam in the Nile River. It brought about significant enhancement in reservoir operations rather than employing a simple Markov model (Tejada et al. 1995).

Tejada et al. (1995) compared SDP models by introducing different policies associated with the value of the hydrologic information. His work concluded that more comprehensive hydrologic information performed better when strict penalties are applied to shortages. Kim and Palmer (1997) carried out seasonal forecast SDP optimization by adopting snow water equivalent (SWE) as a hydrologic state variable to account for snow melt runoff for the Skagit Hydropower System in Washington state.

In recent study by Cote et al. (2011), SWE and soil moisture were used together by alternating from one to the other depending on the season. It was applied to the Hydro-Québec system in Canada and the effectiveness of using hydrologic state variables was compared with the lag-1 SDP model. Desreumaux et al. (2014) used SDP with a single hydrologic state variable by using the real-time SWE as a case study of the Kemano hydropower system in British Columbia, Canada. The general form of SDP which includes the hydrologic state variable was reflected in Tejada et al. (1995) as Equation (2-5).

$$f_{t,}(s_{t,}h_t) = \underset{(q_t|h_t)}{E}\left(\max_{u_t}\left\{B_t(s_t, u_t, q_t) + \underset{(h_{t+1}|q_t, h_t)}{E}\left[f_{t+1}(s_{t+1,}h_{t+1})\right]\right\}\right) \quad (2\text{-}5)$$

$$\forall s_{t,}h_t, t \in \{1,2,\dots,T\}$$

The major steps for carrying out SDP optimization are summarized in Figure 2-6 and each step will be applied into the Bosunggang hydropower plant as a case study in Chapter 3.

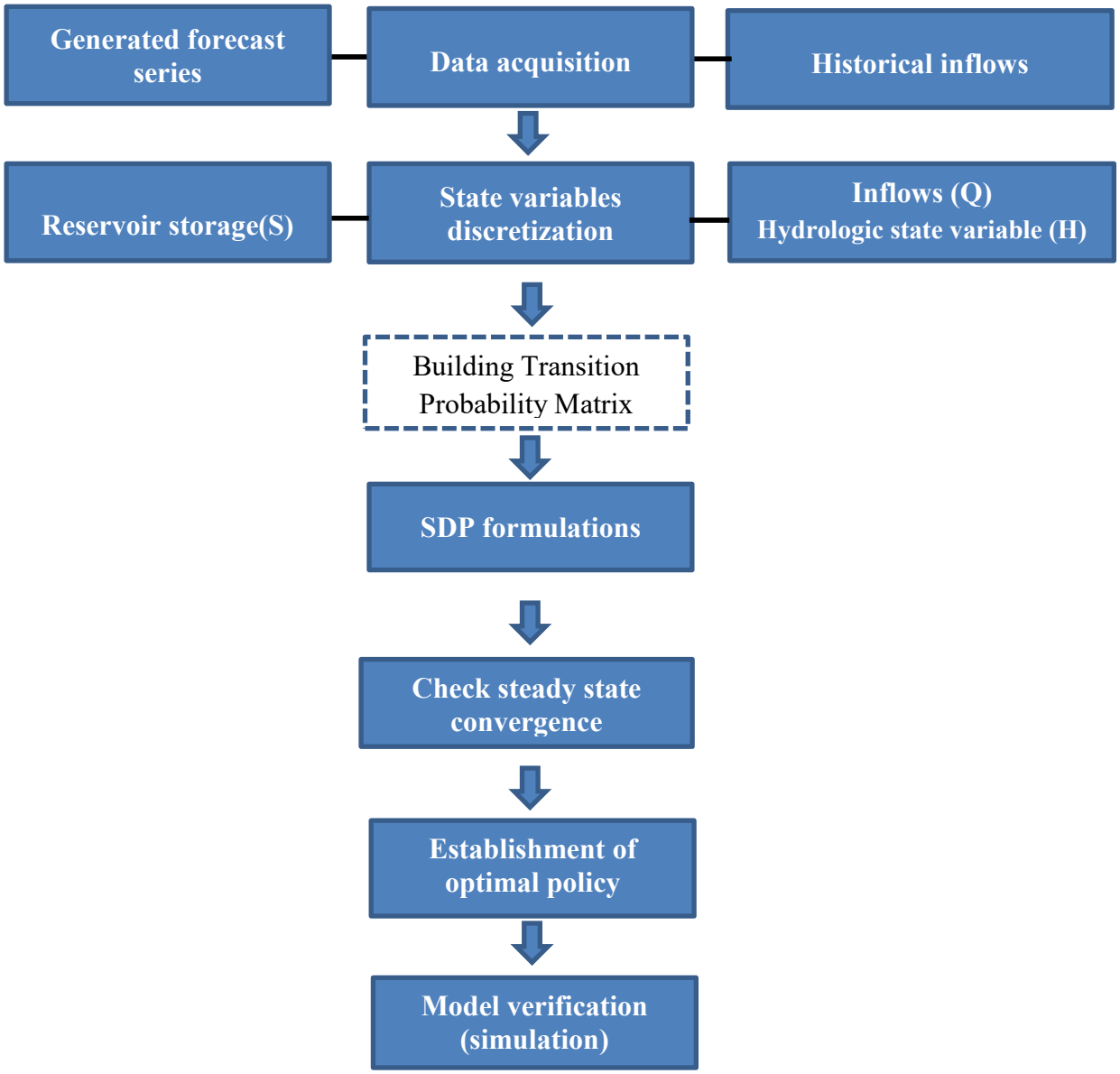


Figure 2-6 SDP reservoir optimization procdures

2.3.2 Sample Stochastic Dynamic Programming (SSDP)

The drawback of SDP mainly lies in its scheme of treating inflows. Once the probability distribution of inflow is built based on the available historical or synthetic inflow generation, it will then be discretized and become state variables in the policy table. However, a key concern is that this partition of inflows may not address extreme inflows such as unexpected drought or a high magnitude flood event, and therefore won't be adequately considered at the phase of building an optimal policy. Thus, due to its limitation in handling out of bound range values in future phases, the resolution of SDP policy can be degraded, for instance, by overestimating benefits (Faber and Stedinger 2001; Tejada et al. 1993; Lamontagne 2015). For this reason, the SDP technique was modified to SSDP by Kelman et al. 1990. SSDP can directly treat more extreme inflows, because this method replaces the discretized inflow probability distribution with a set of time series of historical or future forecast inflows. A number of studies have been performed (e.g., Kelman et al. 1990; Faber and Stedinger 2001; Kim et al. 2007; Vicuna et al. 2011; Eum and Park 2010; Eum et al. 2011; Cote et al. 2011; Lamontagne 2015). The general formulations of SSDP are indicated in Equation (2-6) and (2-7) respectively.

$$\max_{R_t}\left\{B_t(S_t, R_t, Q(i)) + \underset{(j|i)}{E}\left[f_{t+1}(S_{t+1,}j)\right]\right\} \quad (2\text{-}6)$$

$$\forall S_{t,}i, t \in \{1,2,\dots,T\}$$

$$f_{t,}(S_{t,}i) = B_t(S_t, R_t, Q_t(i)) + f_{t+1}(S_{t+1,}j) \quad (2\text{-}7)$$

$$\forall S_{t,}i, t \in \{1,2,\dots,T\}$$

There are two noticeable features to the SSDP technique. First, it can directly incorporate the actual or generated streamflow scenarios into the optimization equation

without the need of partitioning the inflow probability distribution and the use of its representative value as SDP (Faber and Stedinger 2001; Kim et al. 2007). Second, SSDP optimization is carried out by two respective formulations as Equation (2-6) and (2-7); one is for determining the optimal release vector (R), which is the optimal policy to maximize total benefits under uncertainties, and the other equation is to identify value function, $f_t(S_t, i)$ based on the optimal release (R) made from (2-6) without uncertainty. These features of SSDP prevent overestimation of system benefits and simplify stream flow representation, both of which were major limitations of SDP (Kelman et al. 1990; Faber and Stedinger 2001). It is necessary to build a transition probability matrix, wherein inflows of current scenario i are followed by scenario j in the next stage, and this can be derived using the Bayesian concept, and can renew the probability with updated current information (Kelman et al. 1990; Kim and Palmer 1997; Kim et al. 2007; Cote 2011).

In Kelman et al. (1990), the two hydrologic state variables were employed together into to the equation: streamflow forecast (H) and inflow scenario (i). Thereafter, the prior SSDP formulation was modified by considering only the inflow scenario (Faber and Stedinger 2001). It brought about not only a decrease in computational burden but also enhanced model efficiency with regard to preserving empirical joint spatial and temporal correlation between inflows and forecast (Faber and Stedinger 2001). Several related studies had distinctive ways of employing hydrologic state variables. Most recently, SSDP was combined with ensemble stream flow prediction (ESP) (i.e., meteorological forecast technique), to use forecasts as a hydrologic state variable for multi-reservoirs reservoir optimization (Faber and Stedinger 2001; Kim et al. 2007).

In particular, Kim et al. (2007) was the first to apply SSDP/ESP for Korean multi-reservoir systems. After that, Eum et al. (2011) performed research on optimal

drought management using SSDP on the Geum River basin, Korea. However, all previous work related to both SDP or SSDP application in Korean reservoirs did not consider soil moisture as a hydrologic state variable. These authors recommended the use of a hydrologic state variable in SDP or SSDP for future research, and this suggestion was evaluated in this thesis.

The merits of SSDP technique for reservoir optimization are summarized by many researchers (e.g., Kelman et al.1990; Faber and Stedinger 2001; Lamontagne 2015). First, the use of an empirical approach, with the inclusion of series of scenarios, as a means for representing the marginal and joint distribution of stochastic streamflow has been successful at capturing the temporal and spatial correlation of inflows. Second, SSDP allows the consideration of uncertainties in both hydrology and inflows persistence by using separated formulations. As such, the pre-determined optimal course of action from the previous optimization step can be recognized instantly in the following value function computation step.

Curse of Dimensionality

As previously discussed, DDP, SDP, and SSDP are considered to be cutting-edge optimization methods that have been fairly applied in a myriad of fields, such as engineering and ecology. However, the "curse of dimensionality" has been a common challenge for these methods. The problem occurs because, in order to solve these recursive equations, continuous state variables need to be discretized. If multiple reservoir (k) optimizations with the number of N discrete points of each state variable is carried out, N^k points need to be computed (Tejada et al. 1993). This will create significant computational burden to process the proceeding recursive equations. In addition to the number of reservoirs to be addressed, increasing the number of state variable also contributes to the problem, which has been an inherent limitation of DP-based optimization. For this reason, a numerous study has been dedicated to overcoming

such high dimension problems. Several methods to alleviate dimensionality were introduced by others (Johnson et al, 1993; Lamontagne 2015). For example, reduce the number of state variables to make the original problem simpler by aggregation/disaggregation or use efficient searching algorithm to approximate future value function. In addition, modified DP models, such as differential DP and incremental DP, were established to tackle the dimensionality problem (Yeh 1985).

Shor-term Hydropower Optimization

The majority of the reservoir operation studies have been focusing on a long-term policy, such as monthly and seasonal, rather than short-term time step, e.g. daily and hourly, because of its ease of applicability with respect to computational burden and its goal of creating a policy to address long-term seasonal variability. However, this focus results in lowering the flexibility in real-world reservoir operation because of three main reasons: hydrologic uncertainty, market uncertainty, and environmental effects (Olivares 2008; Lamontagne 2015).

First, in small capacity reservoirs, an unexpected increase in the inflow volume which is maintained through the consecutive day can cause critical challenges for operators. It is because this unexpected state (condition) is hard to instantly handle given the long-term reservoir operation policy (Turgeon 2005). Moreover, in the circumstance of random inflows with uncertainties, performance of forecast more than one or two days in advance might be inaccurate in comparison to short-term forecast (Turgeon 2005). Some researchers used a scenario decision tree for addressing short-term hydropower optimization (Séguin et al. 2017). Turgeon (2005) introduced the SDP with multi-lag auto-correlated inflows that are solved by a daily time step. This paper concluded that the multi-lag model is vital for explaining significant correlation in past consecutive days and incorporating the realities of dam operations; operators usually make their decisions in a daily time step with short forecast information.

Therefore, the common assumption in SDP, that current inflow is totally known, may be reasonably supported in daily time step rather than monthly or seasonal long-time step. Secondly, after the power market became liberalized in several countries, energy value needed to be defined as a spot price for each individual short-time step given the fluctuation of electricity demand. This change turned out to be imperative for introducing short-time step optimization into various utility owners who were aiming to maximize the margin from the hydropower generation. Lastly, alteration of the flow regime resulting from controlled natural inflow can be alleviated by short-term operation. Because of the change of inflows, the quantity and quality in the habitat, substrate availability of aquatic and riparian ecosystems are heavily impacted at various time scales ranging from seasonal, to weekly and even hourly (Nyatsanza et al. 2015).

Therefore, with the purpose of minimizing ecological impacts brought by hydropower operation, a short-term operation strategy is highly recommended. The SDP and SSDP with short-term time step (stage) in hydropower plant operations could be a challenging approach because of the calculation burden, but current availability of advanced computer performance can alleviate such obstacle. Many uncertainties in reservoir operation can be effectively reduced by enhancing forecast accuracy by knowing how much inflows will be coming into the reservoir or how long the rainfall will last. So far, reservoir operators may not have difficulties in establishing long-term reservoir policy that has been commonly adopted in multi-purpose dams. However, as unforeseeable future events increase, decisions need to be made instantly. Appropriate operation policy is now essentially required to enhance operation effectiveness with the consideration of market fluctuation, environmental consequence, and other energy capabilities.

2.3.3 Summary

In this section, several types of optimization technique were introduced and compared based on each feature. In particular, the most commonly adopted methods for reservoir optimization are SDP and SSDP, which have proven to be a desirable means for successive decision-making process in hydropower optimization. However, because SDP optimization can take care of hydrologic uncertainty with probability concepts given sufficient data series, it needs ample historical data to generate appropriate optimal solutions. In contrast, SSDP is capable of overcoming this limitation by directly employing inflow scenarios into the optimization process, which is a simpler calculation in comparison to SDP. These physically different aspects will be compared and evaluated in this thesis by performing a case study.

In addition, hydrologic state variables can be included into SDP and SSDP to account for hydrologic persistence. In Korean literature, due to the limitation of acquiring actual long-term, hydrologic state variables such as soil moisture and snowmelt have never been considered in hydropower optimization. This knowledge gap suggests an intriguing research direction for hydropower optimization given the circumstances that actual soil moisture records are not easily available to reservoir optimization. Therefore, in this research, the soil moisture series will be generated by hydrologic model, SSARR, and these outcomes will be included in SDP for case study in chapter 3.

CHAPTER 3 CASE STUDY FOR BOSUNGGANG HYDROPOWER PLANT – EVALUATING POTENTIAL FOR USING SOIL MOISTURE

The study so far has been general considering required minimum environmental flows, and reservoir optimization methods, respectively. Hydropower optimization is an attractive means of getting as much power from a hydropower facility as one can, while respecting environmental constraints. This chapter addresses the issue with a case study, Bosunngang hydropower system, Korea.

3.1 Introduction

In the Bosunggang Hydropower plant (HPP), a new legal minimum environmental flow requirement, 0.47m^3/s, was promulgated by the Korean government on Oct. 30, 2015 for the ecological protection of a major minnow fishery in the Bosungang River. (Government official gazette, 18610). Previously, downstream spills from Bosunggang reservoir rarely occurred except during the flooding season as it has been used exclusively for hydropower since it was built in 1936. However, about 6 percent of the average inflow now has to be released to meet the new environmental flow regulation. There is no way to direct these downstream flows though the turbines, which can be a loss of potential energy generation. Thus, the hydropower plant operation agency, Korea Hydro and Nuclear Power Corporation (KHNP), anticipates a long-term reduction in hydropower generation due to the new constraint. However, a probable alternative, such as installing an additional small hydropower unit to use the environmental releases, could decrease the hydropower energy loss. An extra reason for choosing this system as a case study is that this dam has been operating almost 85 years; its effective reservoir capacity is reduced due to accumulated sedimentation. This has decreased the reservoir's effective capacity which decreases the flexibility of reservoir operations.

This research explores methods that can maximize hydropower production using a daily reservoir operating policy subject to the new legal environmental flow requirements. The case study considers Bosunggang Hydropower plant, the oldest hydropower plant in Korea. Hence, in the following section, cutting edge reservoir optimization methods, Stochastic Dynamic Programming (SDP) and Sample Stochastic Dynamic Programming (SSDP) will be evaluated. The expected outcomes could lead to improving efficiency of existing hydropower operations under the ecological constraint. The specific objective of this chapter is to evaluate the potential use of watershed soil moisture data for use in SDP/SSDP models.

Figure 3-1 Downstream of Bosunggang reservoir, zone of minimum environmental flow at the point of Gym-bak and Juk-kok.

3.2 Study System: Bosunggang Hydropower System

Bosunggang dam is the oldest hydropower plant in Korea at present, which was built in the period of Japanese occupation, 1931 to supply water to the Deuk-lyang reclaimed land for irrigation purpose. After 1931, this dam was owned by a Japanese company that installed an electrical penstock for hydropower generation in 1937. Since then, this reservoir has been used solely for hydropower production. In 1960, management was taken over by KHNP, which is owned by the Korean government. Figure 3-2 illuminates the Bosunggang HPP's location and its general views.

Figure 3-2 Location of Bosunggang hydropower plant and its relevant view

Figure 3-3 summarizes the energy sector in South Korea: The majority of energy source is natural gas (33%), coal (28%), and nuclear (22%). Installed capacity of hydropower accounts for 6,471MW with 5,931Gwh, 7% of the total energy capacity. Fossil fuels generated about 64% of South Korea's electricity generation in 2015, while 31% came from nuclear power, and 5% came from renewable sources, including hydroelectricity. Although fossil fuel-fired capacity is now dominant in South Korea, nuclear power is also a baseload power source (U.S energy information administration, 2017). Hydropower in South Korea accounts for peak load, and systems are owned by two different governmental agencies, K-WATER and KHNP.

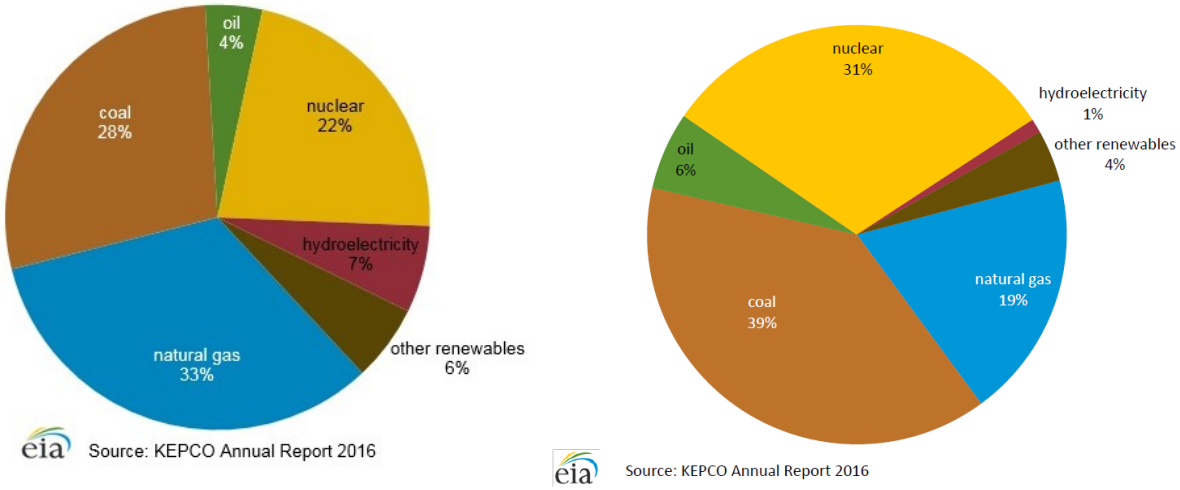


Figure 3-3 South Korea installed capacity (left) and generation in 2015(right) by energy type, (EIA report,2017)

Critical physical attributes of the Bosunggang HPP system are summarized in Table 3-1.

	Bosunggang HPP	Scheme
Average yearly Precipitation (mm)	1,280	
Average daily inflow (m^3/s/day)	9.4	
Active storage (MCM)	4.7	
Watershed area (km2)	267	
Hydropower capacity (MW)	4.5 (2.25 x 2 unit)	Francis
Maximum turbine release (CMs)	6.4	
Annual power generation (GWh)	21	
Maximum release capacity (CMs)	2,419	
Dam Type	Concrete gravity	H=11.88m, L=274
Type of spillway	Tainter gate	12 gates

Table 3-1 System features of Bosunggang HPP

Bosunggang hydropower system is a relatively small reservoir compared to its annual inflows; active capacity of reservoir is 4.7MCM and average daily inflow is 0.8MCM. Storage capacity can be represented by the ratio of storage capacity and average inflows, which denotes the time for filling the reservoir to the full level from empty condition: this factor of capacity of Bosunggang reservoir is 7days.

Geo-spatial analyses of the physical characteristics of the upstream watershed were conducted, including distribution of elevation, slope, soil type, and land-use (Figure 3-4). The watershed area of Bosunggang HPP is 267km^2 with an average slope of 23%, and an average elevation of 227 EL.m. The land-use in the watershed is composed of forest (58%) and agriculture (29%). The major soil type in this watershed

is Mangum (Ma) (52%), which is a Lithosol (a group of shallow soils lacking well-defined horizons, usually on steep slope), consisting of siliceous crystalline material. These have high permeability and are usually dissected hilly and mountainous lands (Korea Rural Development Administration).

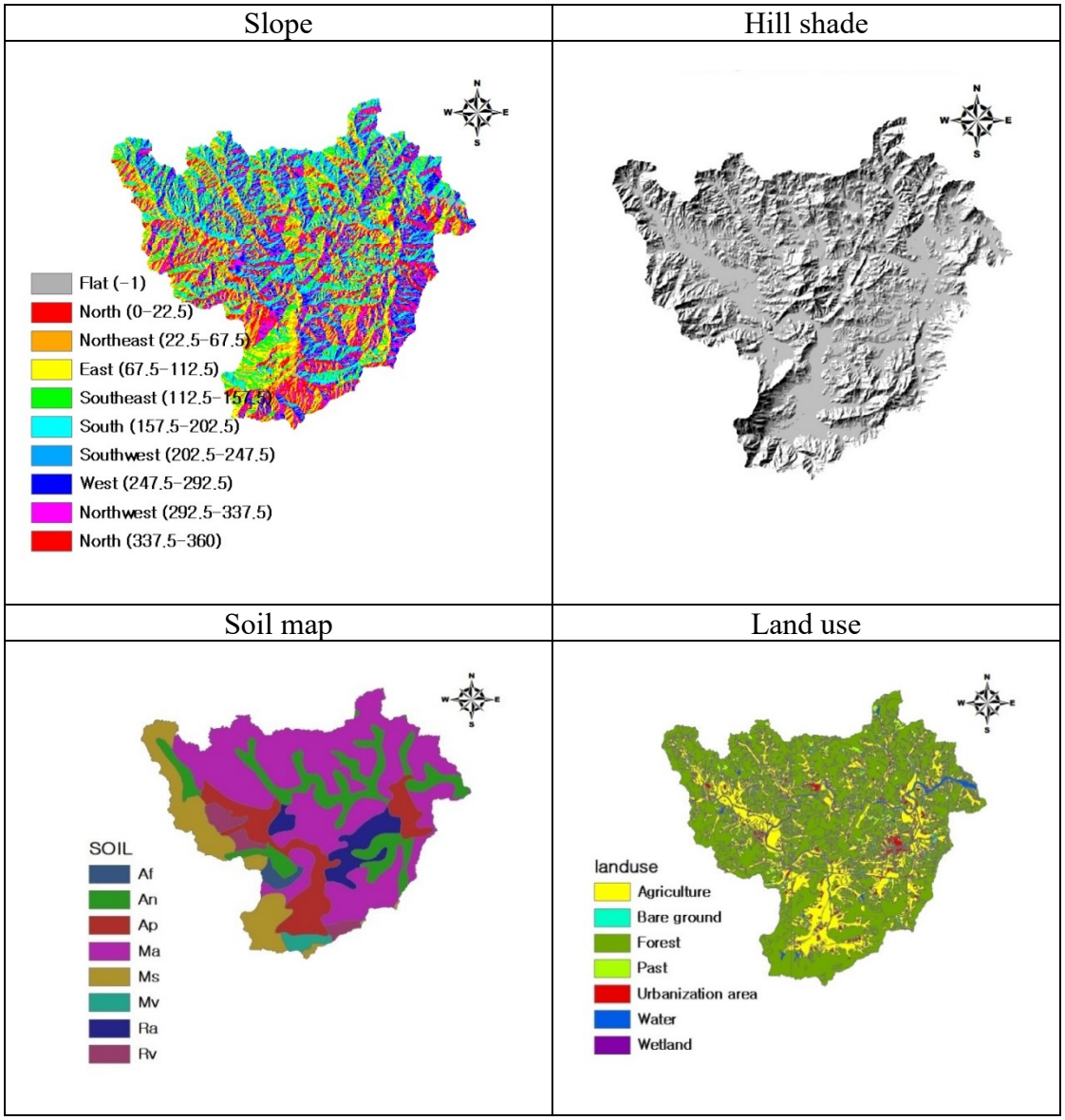


Figure 3-4 Watershed characterstics of Bosunggang HPP

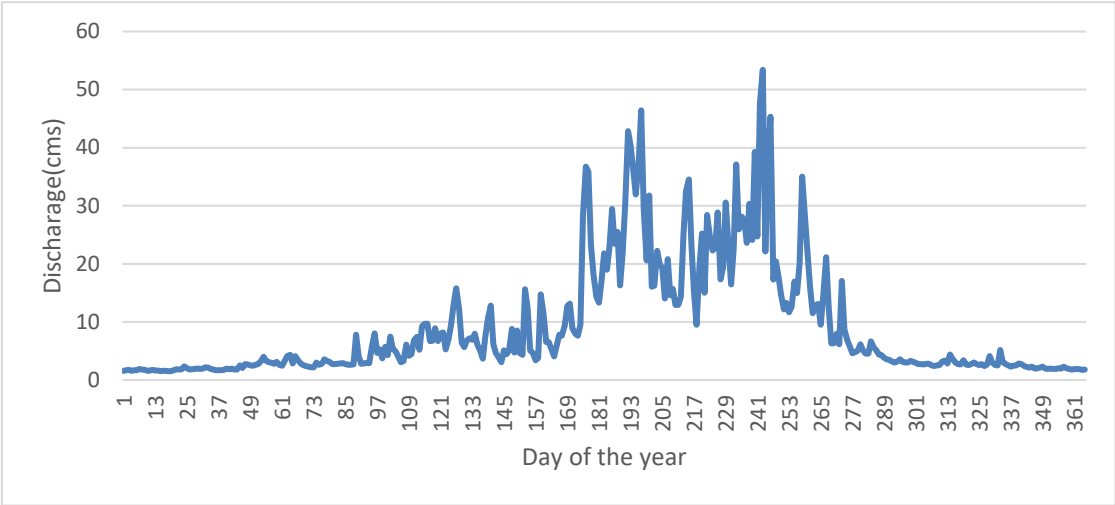


Figure 3-5 Daily mean inflows into the Bosunngang reservoir (51years)

The annual precipitation in the Bosunggang HPP catchment is 1,280mm, with an average daily inflow of 9.4 m^3/s. As is typical throughout Korea, the hydrologic feature in Bosunggang watershed exhibits a distinguished seasonality as shown in Figure 3-5,. The stream flows reflect the typical weather characteristic of a monsoon period from July to September in which over 60% of the annual precipitation falls during 3 months (Kim et al. 2007).

For the power generation, Bosunggang HPP diverted water from the reservoir to a powerhouse through the 2.2 km penstock with an 83.65m effective water head (Figure 3-6). The installed total capacity of the powerhouse is 4.5MW with two Francis water turbines and annual average power generation is about 21 GWh. As such, though the installed capacity is relatively small, power efficiency is beyond 50%, and the generated electricity is supplied to the surrounding area of Bosung-gun district for about twenty thousand households. The dam is equipped with twelve tainter gates to spill excessive inflows and required environmental flow to the downstream.

Figure 3-6 View of power house (Left), penstock to power house (Right)

The Multi-reservoir system on the Bosunggang river consists of two separate dams constructed for different purposes; one is the hydropower plant, Bosunggang HPP, and the other is multipurpose dam, Juam dam, managed by another reservoir owner, K-Water, which has two reservoirs connected through the water conduction tunnel. In this study, however, only the Bosunggang HPP with a single reservoir will be discussed as a case study. A schematic of the entire system is shown in Figure 3-7.

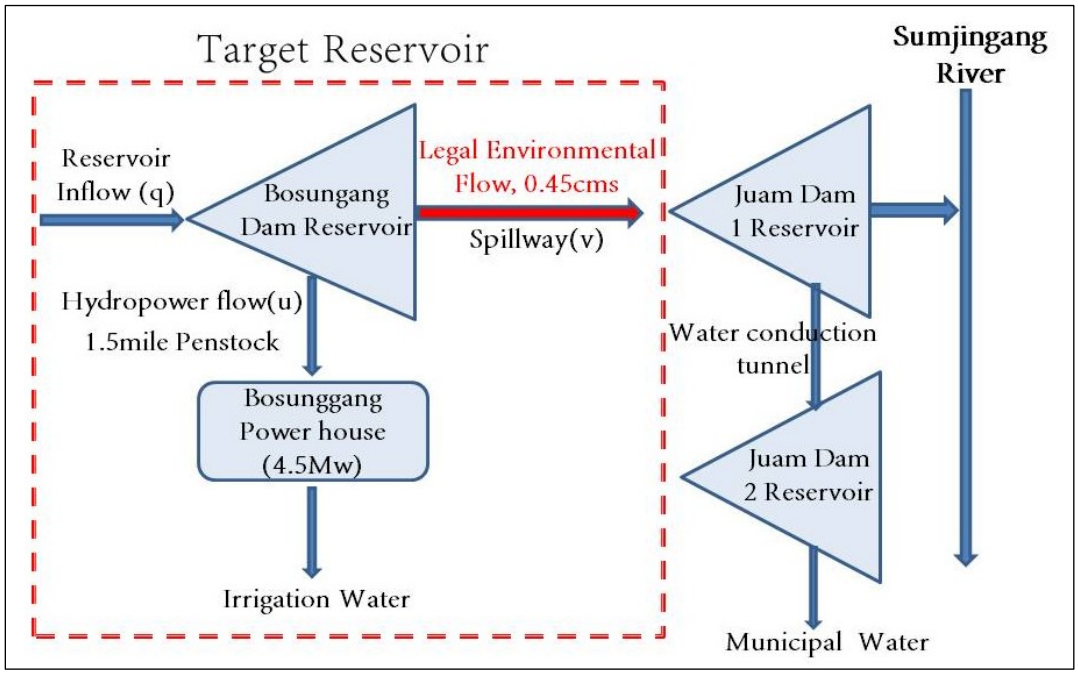


Figure 3-7 Schemetic diagram of the Bosunggang hydropower system, Korea

3.3 Methodology

The overall process for evaluating hydropower operations in the case study for Bosunggang HPP will be carried out as depicted in Figure 3-8.

(1) Generate a daily soil moisture time series using the hydrologic model

- Streamflow Synthesis And Reservoir Regulation (SSARR), US Army Corps of Engineers, 1991

(2) Implement hydropower optimization: Stochastic Dynamic Programming (SDP) and Sample Stochastic Dynamic Programming (SSDP)

(3) Identify optimal policy for daily turbine release

(4) Simulate identified policy.

This Chapter 3 addresses Step 1 – evaluating the use of a daily soil moisture time series for use in the optimization models.

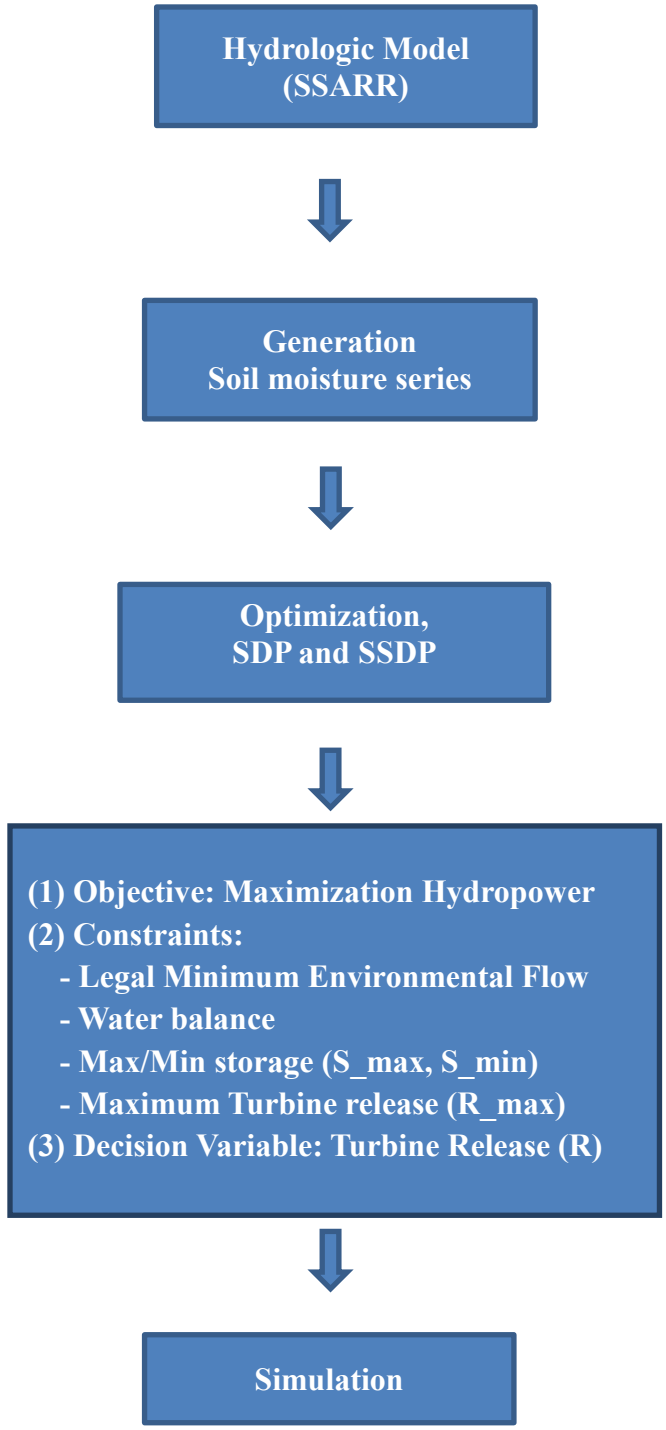


Figure 3-8. Flow chart of case study implementaion

Hydrologic State Variable

The choice of a hydrologic variable could improve optimization performance under a wide range of hydrologic phenomenon in hydropower system (Stedinger et al. 1984; Tejada-Guibert et al. 1995; Côté et al. 2011). In the absence of hydrologic state variable in DP, inflows from one period to the next are assumed to be independent, and temporal persistence is not modeled. The two most common choices for hydrologic state variable have been the current inflow (Q_t) and the previous flow (Q_{t-1}). Those two models have been successfully represented as a Markov process, and compared each other to examine its impacts on optimization performance (Stedinger et al. 1984; Kelman 1990; Huang et al. 1991; Tejada-Guibert et al. 1995; Kim et al. 2011).

Recently, as an expanded work, a set of generated hydrologic state variables such as Snow Water Equivalent (SWE) or soil moisture (e.g., Côté et al. 2011; Desreumaux et al. 2014) were taken into account to improve predictions of future inflows as well as to consider hydrologic persistence in the inflows series. The case study in this chapter conceptually followed the methodology developed in earlier studies for soil moisture content, while adopting daily time step. Variations in the optimization (i.e., state resolution, and hydrologic state variable) and system characteristics (i.e., turbine and objective) were also considered.

In the region, soil moisture series generated by using hydrologic model, SSARR, will be incorporated into SDP as a hydrologic state variable. Although actual historic records of soil moisture in case study area are available for 5 years, from 2010 through 2015, all data cannot be used for this study except 2014 due to a number of missing data in other years.

A second watershed model, SWAT, will then be run as a comparison for generating stream flow. Stream flow outputs from both models will then be compared with actual stream flow records for a single year to assess success.

3.3.1 Generation of Hydrologic State Variable, Soil moisture

Various methods for generating soil moisture series were evaluated and several run-off hydrologic models were reviewed. It is important to choose the appropriate model among a variety of models available. The model's output will be used in the reservoir optimization work as the hydrologic state variable. A comparison of runoff simulation models commonly adopted in Korean watersheds was conducted by the Ministry of Agriculture, Korea (2015). This study shows that SSARR was the most accurate in terms of precision of forecast for Korea.

In 1956, the mathematical and hydrological model, SSARR was introduced with the aim of managing water resources systems in the in the North Pacific Division of the U.S Army Corps of Engineers (USACE 1991). The applicability of this model has long been demonstrated in world-wide: the Columbia River in the United States by Nelson and Rockwood (1971) and Mekong River in Vietnam Rockwood (1968) (Lee et al. 2012). In Korean studies, especially, Kim et al. (2007) employed the SSARR to generate Ensemble Streamflow Prediction (ESP) scenarios in SSDP reservoir optimization for Han river case study, Korea. Accordingly, the SSARR model was chosen in this research to generate daily soil moisture series, since successful precedent applications were widely demonstrating its capability for dealing with complicated soil moisture behavior.

SSARR Model

There are two different versions of SSARR, the Depletion Curve (DC) version model and the Integrated Snowband (IS) version model. The latter model was adopted in this study; it is capable of performing analysis for runoff interpretations with the consideration of altitude, soil moisture and meteorological components under numerous time intervals. The major parameters used for calibration are SMI (soil moisture index), ETI (evapotranspiration index), and BII (baseflow infiltration index), which are

presented in the form of indices. One of the considerable merits of using SSARR is that the model segregates snow and water from the soil with respect to elevation, by dividing the total altitudinal change into several designated intervals or bands. The conceptual process of the model for runoff analysis is briefly discussed here based upon Lee et al. (2012).

(1) Respective precipitation and temperature are calculated relevant to each band.

(2) The rain and snow volumes are divided based on temperature, after first subtracting out interception captured amounts.

(3) The total sum of precipitation and snowmelt is diverted to either soil moisture or to runoff based on Soil Moisture Index (SMI) which rates the percentage runoff dependent on condition of soil.

(4) The runoff is divided into direct runoff and base flow by the baseflow infiltration index (BII). The direct runoff is then split into two surface flows, above–surface runoff and below surface runoff respectively based on subsurface separation (S-SS). The base flow is also split into underwater runoff and return underwater runoff according to lower zone.

Figure 3-9 illustrates the process of simulating SSARR model from beginning steps, preparation of input data, through the snowmelt and soil moisture assessment, and finally reaching to run-off outcomes.

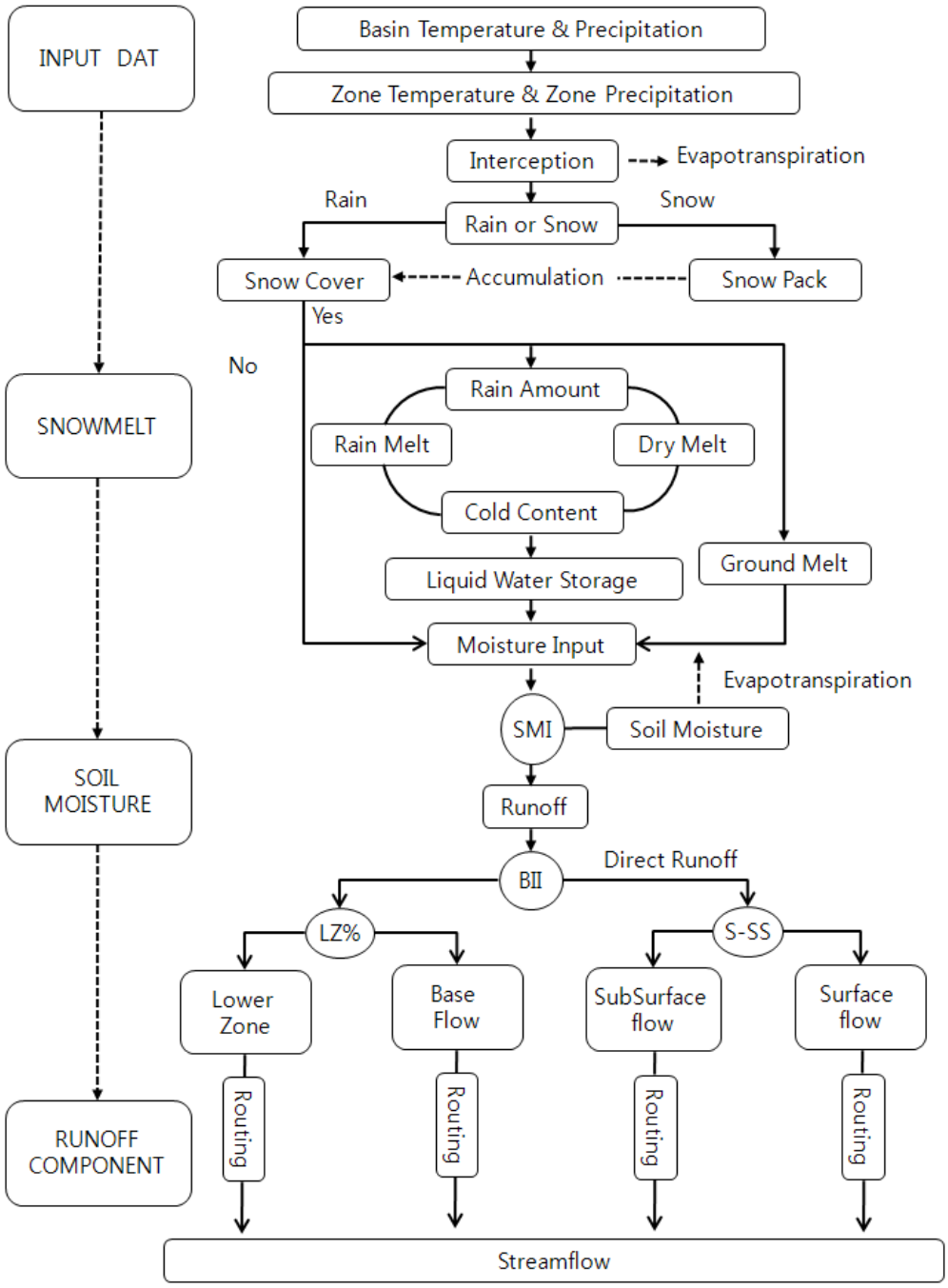


Figure 3-9 Diagram of SSAR Model (USACE 1991)

Although the IS model is capable of simulating snow for which several relevant information is required such as snowpack data and depth of snowfall, these data are rarely available in the Bosunggang case study area, but we also assumed that snow effects in runoff were not significant. Thus, in this study, the component of assessment for snowmelt was excluded.

Model Parameters

Parameters required to run SSARR model are directly derived from current research outcomes on the adjacent area (14km from Bosuggang HPP) conducted by one of the Korean governmental agency in which the SSARR was adopted as a base run-off model: Water budget analysis and establishment of integrated master plan for Yeongsangang watershed, Ministry of Agriculture, Food and Rural Affairs and Korea Rural Community Corporation, 2015. Thus, it can be seen that parameters used in recent study could be valid in directly applying to this case study except hydrological and geometrical variables pertaining to Bosunggang reservoir condition (e.g., basin area, precipitation, and temperature).

(1) Physical parameters

A single watershed band was adopted for this study.

(2) Hydro meteorological parameters

Records of daily rainfall and temperature are available for Bosunggang HPP by operation agency, KHNP, and a total of 51 years of historical records were acquired, and used as input parameters for the SSARR run-off simulation. Nearly all the rain occurs during the summer monsoon, as shown in Table 3-2.

	Month											
	1	2	3	4	5	6	7	8	9	10	11	12
Temperature (℃)	2	4	7	12	17	20	24	24	20	16	10	4
Precipitation (mm)	2	6	9	13	15	13	18	21	14	9	6	3

Table 3-2 Monthly average temperature and precipitation, Bosung HPP

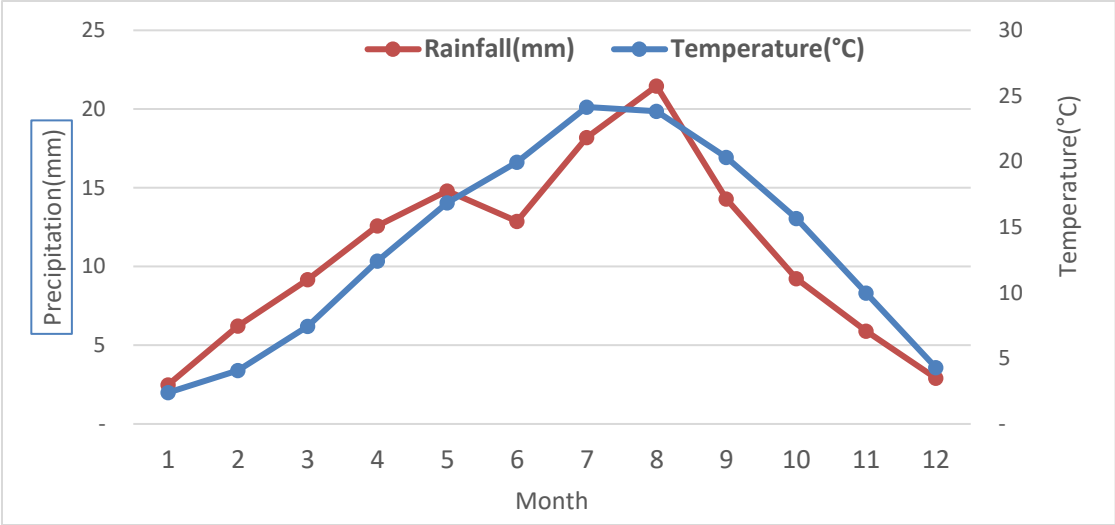


Figure 3-10 Monthly average temperature and precipitation

The parameter, rainfall Weighting of Altitude parameter (ELPP) was defined to take care of limitation that rainfall will be equally distributed along the whole elevation. The parameter of ELPP were derived from previous governmental research outcomes (Optimal reservoir management development report in Nakdong-river, K-WATER, 1996), and shown Table 3-3.

Parameters for ELPP

Parameter	Rainfall weight (%) along the height (m)							
	0	200	400	600	800	1,000	1,200	1,400
ELPP	99	100	100	101	102	102	103	103

Table 3-3 ELPP parameter

Other hydrometeorology parameters related to evaporation are reported in Table 3-4 and Table 3-5. The ETM parameter is used to calibrate the monthly evapotranspiration value by incorporating latitude information.

Parameters for KE, ETP, DKE, ETEL

Rain fall intensity (cm/day)	EKE (%)	Temperature (°F)	ETP (cm/day	DKE (%)	Height (m)	ETEL (%)
0	100	20	0	0	0	100
2	50	30	0	50	400	100
3	20	40	0.10	90	800	110
5	10	50	0.20	100	1,200	120
10	10	60	0.30		1,600	130
	10	80	0.45		2,000	140
		100	0.60			

Table 3-4 parameters for KE, ETP, DKE, ETEL

* EKE: Rainfall intensity versus evapotranspiration parameter

* ETP: Temperature versus evapotranspiration index

* DKE: SMI versus evapotranspiration weight index

* ETEL: Elevation adjustment factor versus evapotranspiration weight

Parameter for ETM

Month	ETM(%)	Month	ETM(%)	Month	ETM(%)
Jan	86	May	122	September	103
Feb	84	June	123	October	97
March	103	July	125	November	85
April	110	August	117	December	83

Table 3-5 parameter ETM

* ETM: Weight factor of evapotranspiration index

(3) Process Parameter

The process parameter is mainly comprised of soil moisture–runoff percentage (SMI-ROP), BII versus base flow percentage (BFP) and surface flow versus subsurface flow (S-SS). Among above parameters, the SMI-ROP has been shown to have the most significant effects on the simulation. The parameters from Table 3-6 to Table 3-9 are derived by from SSARR manual (p. C-4).

Parameters for SMI-ROP

SMI (cm)	0	1	2	3	4	5	10	999
ROP (%)	7	17	39	62	79	87	100	100

Table 3-6 parameters for SMI-ROP

Parameters for BII – BFP

BII (cm/day)	0	1	1.5	2	2.5		3	5.0	100
BFP (%)	44	16	14	12	11		10	10	10

Table 3-7 parameters for BII – BFP

Parameters for S-SS

Input Rate (cm/hr)	0.0	0.5	1.0	1.5	2	2.5	3.0
Surface Comp(cm/hr)	0.00	0.25	0.75	1.25	1.75	2.25	2.75

Table 3-8 parameters for S-SS

Additional parameters

BIITS	BIIMX	BFLIM	PBLZ	DGWLIM
40hr	3cm/day	0.13cm/hr	50%	0.1cm/hr

Table 3-9 Additonal parameters

In practice, setting the initial value of each of the parameters is followed by calibration of those parameters based on objective function, minimizing the errors between outflow of observed records and modeled values. However, this calibration work could be avoided because it was assumed that this study directly used parameters which were calibrated from former government research, Yeongsangang (2015) conducted on nearby watershed.

3.3.2 SSARR Simulation

Once all required parameters were prepared, the remaining work was to simulate models to obtain value of outcomes, which are soil moisture series in this study. The simulation was carried out for the 51years period from 1965 to 2015. The model performance was then evaluated based on the value of the difference between the inflows generated by the model and actual inflow records using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE= $\frac{1}{N}\sum_{i=1}^{n}|prediction - observed|$) (Chai and Draxler 2014).

3.3.3 SWAT Simulation

As an additional independent test, an alternative soil-based runoff model, Soil Water Assessment Tool (SWAT), was also applied. Hydrologic modeling of the reservoir in question can be accomplished to a specified degree of accuracy using a combination of both Arc-GIS and the Arc-SWAT modeling software component. SWAT is an open-source software published and maintained by the United States Department of Agriculture's (USDA) Agricultural Research Service.

Figure 3-11 indicates the scheme of SWAT.

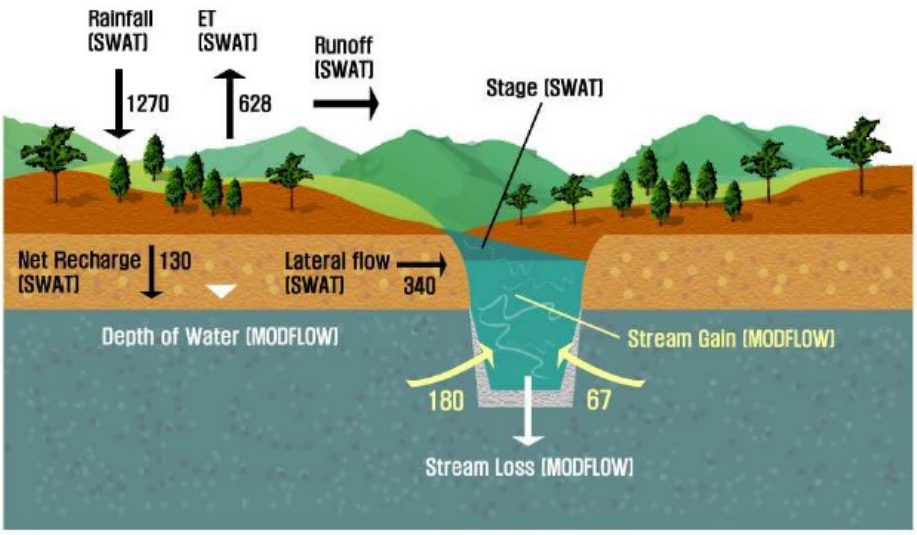


Figure 3-11 Schematic of SWAT model
(source: Korea Institute of construction technology)

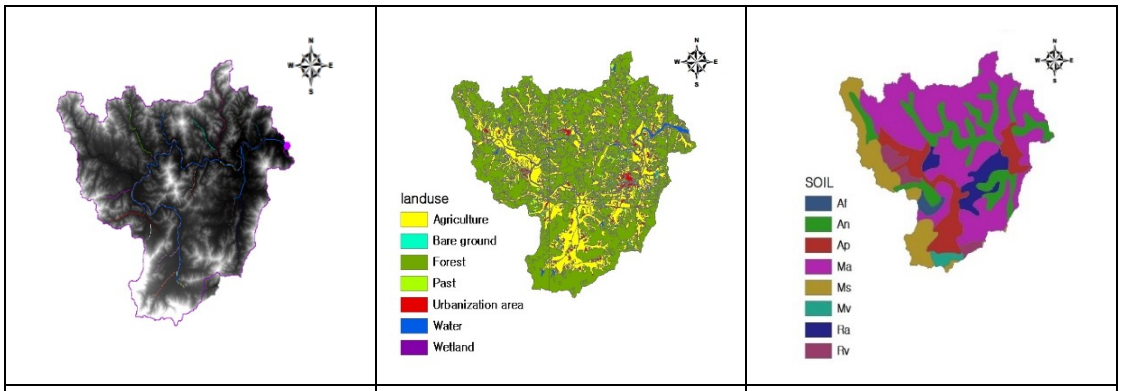
Two main procedures are required to carry out SWAT simulation: 1) calculation of the water balance of each Hydrologic Response Units (HRUs) to account for water available for each sub-basin, 2) channel routing phase (Neitsch et al. 2002; Troin and Caya 2014). ArcGIS maintains functionality for incorporating the SWAT model using their interface to ease the translation of geographical information. Input data for SWAT analysis is as below.

1) Meteorological data (daily)

- Temperature, precipitation, solar radiation, inflows, humanity (source: KHNP).

2) GIS data (Figure 3-12)

- DEM (Digital Elevation Model, 30m*30m)
- Land use map (source: Korea water management system, WAMIS)
- Detailed soil association map, 1: 25,000 (source: Korea rural administration)



DEM	Land use	Soil

Figure 3-12 Input GIS data for SWAT MODEL

3) Parameters

The parameters for SWAT model were used not calibrated in this study, instead used default values. For future study, it needs more careful calibration procedures to improve model accuracy.

Model Comparison (SSARR versus SWAT)

Although both SSARR and SWAT hydrologic models have been commonly applied to continuous rainfall–runoff response at the catchment scale, its differences exist in relation to representation of hydrological process (Troin and Caya, 2014).

	SWAT	**SSARR**
Model structure	Process based	Conceptual
Spatialization	Semi-distributed	Lumped
Runoff generation	Soil Conservation Service Curve Number method	Empiric relationship between soil-moisture index and runoff percent
Baseflows	Recession function	Baseflow infiltration index
Channel routing	Variable storage routing method	Muskingum method
Evapotranspiration	Priestley–Taylor method	Thornthwaite method

Table 3-10 Conceptul differences between SWAT and SSARR (Troin and Caya, 2014 table 1,)

SSARR could represent watershed configuration more detailed using an elevation band. Whereas, SWAT uses theoretical relationship using depletion curve: "depletion curve treats the watershed as an entity, whereas the elevation band method maintains an inventory of snow water equivalent and soil-moisture parameters for each elevation band" (Troin and Caya, 2014, page 1862).

3.3.3 Model Results

Simulation result using SSARR and SWAT were compared to actual record in year 2014 (Figure 3-13).

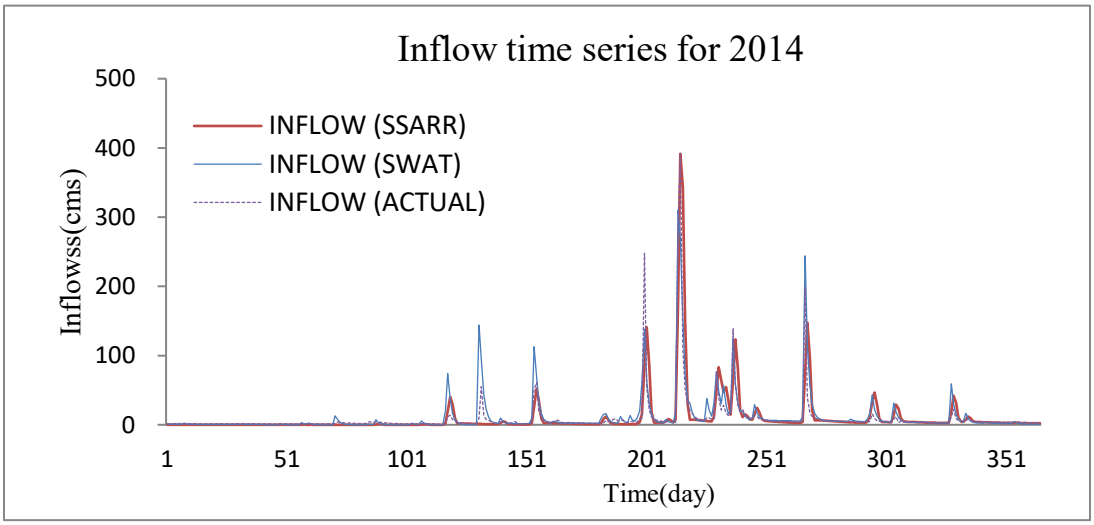


Figure 3-13 Hydrologic model comparion of output from SSARR vs. SWAT vs actual flow pattern for 2014

The result shows very good agreement in the time series trend with performance value of RMSE (22.2 m^3/s) and MAE (6.5 m^3/s) for SSARR; RMSE (14.9 m^3/s) and MAE (4.7 m^3/s) for SWAT. Although the SWAT shows relatively lower error based on run-off simulation, the ultimate outcomes of using these models was to obtain daily soil moisture series. In addition, the SSARR has advantages in dealing with soil moisture

behavior precisely by adopting elevation band (Troin and Caya 2014). As a result, SSARR will be used to generate soil moisture series in this research.

As shown in in Figure 3-14, both daily inflow and soil moisture time series generated by SSARR model were highly correlated, RMSE (22.2 m^3/s) and MAE (6.5 m^3/s), with the actual stream flow records in relation to peak flows.

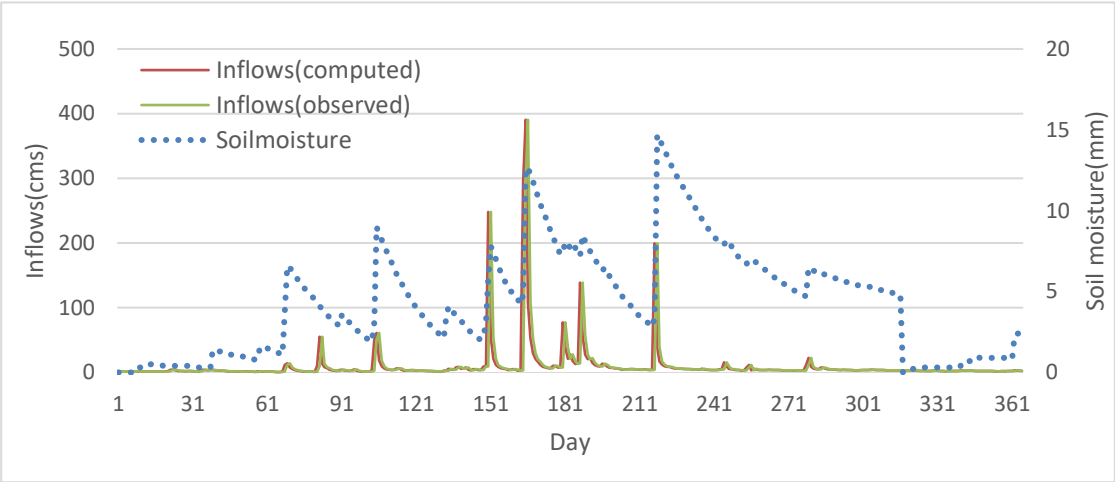


Figure 3-14 Simulation result (SSARR) of inflows and soil moisure in 2014

Additionally, the hydrologic relationship between inflows and the generated soil moisture was reasonably captured: the peak outflows correspond to the time of occurrence of peak moisture. The computed inflows and observed inflows are also well matched in terms of both the seasonal timing and the magnitude of the peak flow events when considered on a daily basis. This comparison also shows clearly that there is a slower time lag in the decline in soil moisture content as compared with the stream flow recession. This time lag appears to accumulate and when averaged on a monthly basis, the comparison between soil moisture patterns and stream flow are less well correlated (RMSE is 3.9 m^3/s and MAE is 2.8 m^3/s).

Figure 3-15 shows monthly basis time series for observed, computed, and soil moisture series.

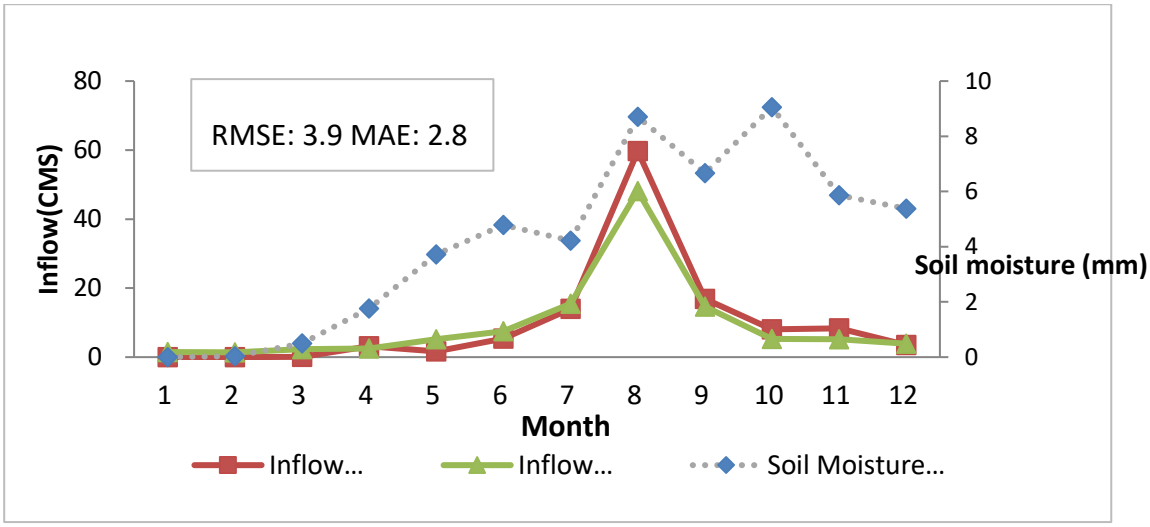


Figure 3-15 Monthly inflow and soil moisture time series in 2014yr

Based on the simulation results, it can be concluded that generated soil moisture series using SSARR can become a reliable alternative to real measurement in the absence of real soil moisture records. Runoff has generally close relationship with soil moisture in hydrology mechanism, thus, 51 years of generated soil moisture time series can be used to model in this case study as a forecast component in the optimization.

3.3.4 Summary

The SSARR, hydrologic model, was used to generate soil moisture series for 51 years in this chapter. In fact, the most important phase in performing hydrologic model is parameter calibration to build accurate model. However, this study directly used calibrated parameters derived from former research outcomes in adjacent area. In the future, careful model calibration will be recommended. In addition, due to the lack of actual soil moisture records, the model performance was evaluated by stream flows records. This limitation can be addressed later, if more actual soil moisture data will be available.

CHAPTER 4 OPTIMIZATION APPLICATION

The goal of this Chapter is to develop both the SDP and SSDP optimization models for the Bosunggang hydropower operations. The models include the environmental flow constraint. The analysis then compares the model outputs to determine whether there are significant differences between the policies derived with either model, and the 'historical operation" policy.

4.1 Model Assumptions

In this study, several assumptions were adopted to define the characteristics of the system. The assumptions made in building an optimization model are:

(1) Existing turbine can work at maximum level whenever system constraints (e.g., maximum storage, minimum storage) are honored;

(2) The soil moisture in the upstream drainage basin for the Bosungang River has a direct impact on the associated reservoir inflows as measured on a daily time basis;

(3) Current flow is known in both SDP and SSDP formulation at each stage;

(4) The priority for this reservoir is to maximize hydropower generation (or the values of power generated) while meeting the legal environmental minimum flow, which will be defined as a foremost constraint in this research;

(5) The target reservoir has two outlets in which outflows are diverted to different directions; one is releases through the turbine for power generation and finally runs into ocean. The other spills to the downstream of storage reservoir via the Bosungang River through outlet gates.

4.2 Model Development

4.2.1 Data Normalization

The actual daily inflow record for Bosunggang reservoir for 1965~2015 (51yrs) was acquired from the hydropower agency, KHNP (Korea Hydro and Nuclear Power Corporation). Hydrologic stream inflow distributions generally tend to be skewed, whereas the simple Normal distribution has skew of 0. Analytical methods to check the normality are available in the Stochastic Analysis, Modeling, and Simulation Program (SAMS 2007, Colorado State University, 2007) as part of its stochastic analysis tool. This tool includes two major normality tests: one is a skewness test of normality (Snedecor and Cochran, 1980), and the other is a Filliben probability plot correlation test (Filliben 1975; Sveinsson et al. 2007). These two tests were applied to both the acquired 51 years of inflows and to the soil moisture series that was generated by SSARS in Chapter 3.

Results of Normality Tests

Based on these two tests, the degree of skewness was significant throughout the entire record for both the inflows and soil moisture series (Figure 4.1 to Figure 4.4). The Filliben test calculates the correlation between the ordered observation and their corresponding fitted quantiles; high correlation values (above 0.95) demonstrate that data records are derived from a normal distribution (Filliben 1975; Vogel 1986; Loucks et al. 2005). Given the skewness test for original daily inflows, 360 days out of total 365 days are rejected, and 358 days out of 365 days are rejected based on the Filliben test. For soil moisture series, 201 days for skewness test and 188days for Filliben test were respectively rejected (Table 4-1). As a result of these findings, it was determined that the data would need to be transformed. For the flows on each day of the year (365 different days) a different transformation was developed.

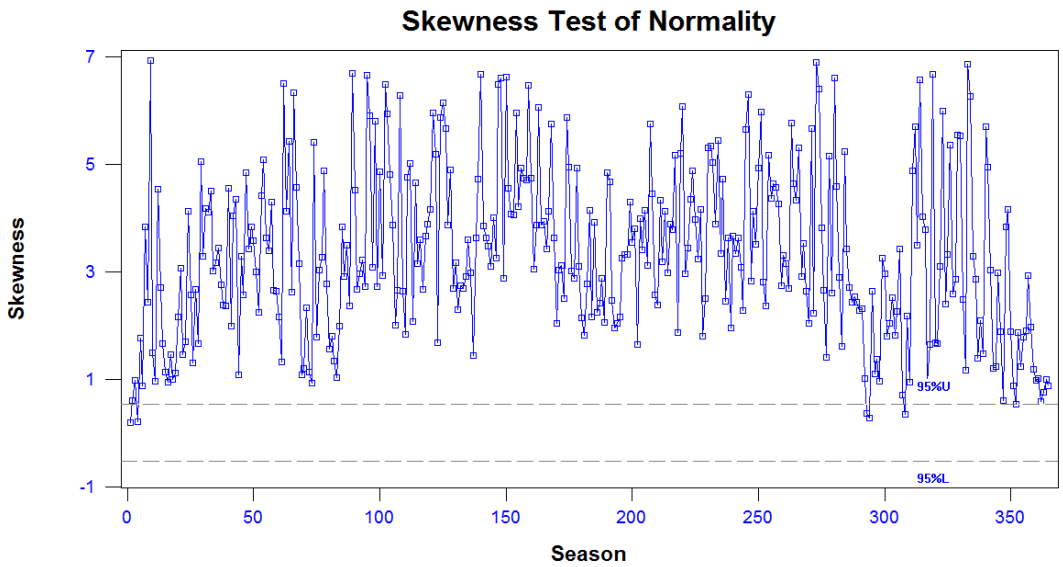


Figure 4-1 Skewness test of normality for inflow

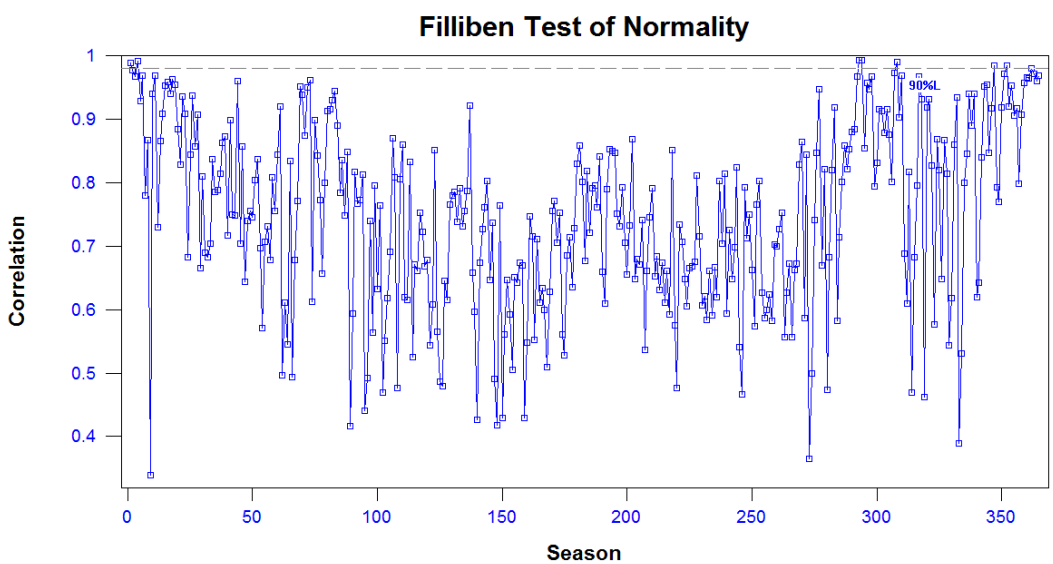


Figure 4-2 Filliben test of normality for inflow

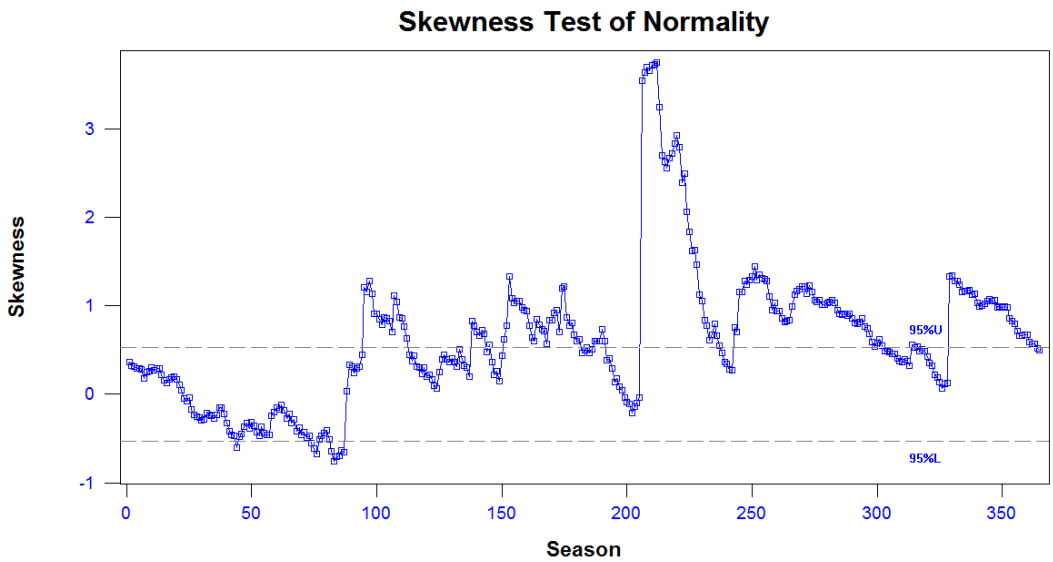


Figure 4-3 Skewness test of normality for soil moisture

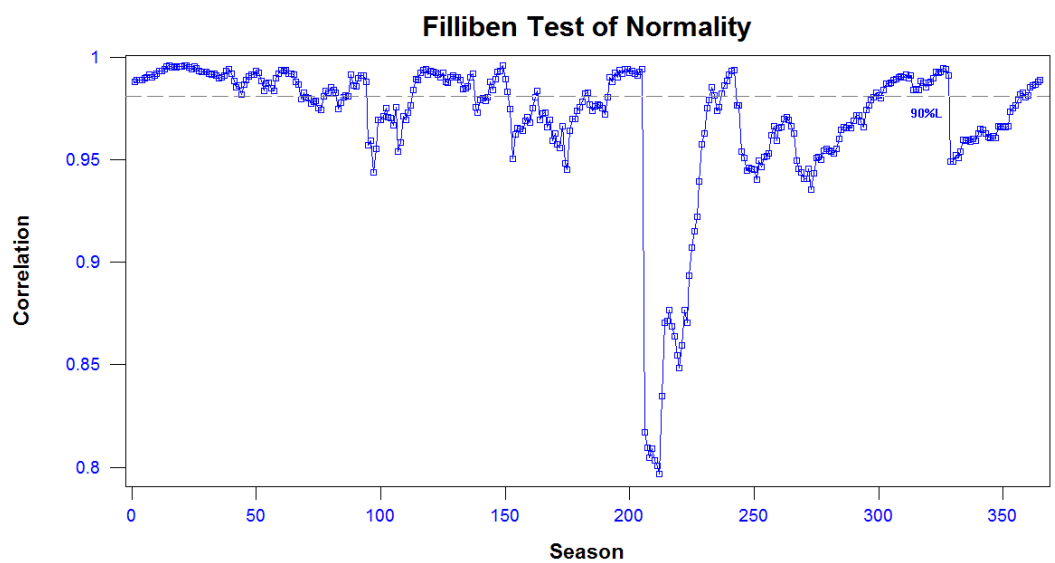


Figure 4-4 Filliben test of normality for soil moisture

Software programs to achieve the normal transformation are readily available from SAMS 2007, which includes a convenient function for recommending the best fitted distribution with related parameters based on criterion of the two normality tests. In this study, the log transformation is selected as the strategy for normalization of the inflows. For the generated hydrologic state variables, the both lognormal and power transformation were alternatively employed. The following are equations for respective transformation.

$$\text{Lognormal Tranformation: } \mathrm{Y} = \ln(\mathrm{X} + \mathrm{a})$$

$$\text{Power Transformation: } \mathrm{Y} = (\mathrm{X} + \mathrm{a})^{\mathrm{b}}$$

Where, Y: the normalized serial data,

X: original skewed data

a, b: transition parameters

Parameter a in lognormal transformation is calculated Equation (4-1) (Stedinger 1980)

$$a = \frac{x_q x_{1-q} - (x_{0.5})^2}{x_q + x_{1-q} - 2x_{0.5}} \tag{4-1}$$

Where, $x_q = largerst\ observation$

$x_{1-q} = smallest\ observation$

$x_{0.5} = median\ value$

In addition, parameters for power transformation, a and b, are estimated by an iterative process aimed at maximizing the Filliben correlation coefficient test statistic (SAMS 2007 manual p.90). As a result of applying transformation on the skewed inflows as well as soil moisture series, the skewness initially embedded in the times series data was significantly reduced (Table 4-1 and Figure 4-5 to Figure 4-8). Additionally, the normal probability plots were generated for stream inflows and soil

moisture from one sampled date: January 27 and February 8 (from Figure 4-9 to Figure 4-11). These demonstrated the approximate normality of the two data sets. Several studies addressed calculation of the parameter a in LN3 transformation (e.g., Sangal and Biswas 1970; Stedinger 1980). Normality performance can be improved with better parameter estimation method.

	Inflows		Soil moisture	
Normality Test	Before	After	Before	After
Skewness test	360	6	201	0
Filliben test	358	171	188	14

Table 4-1 Normality test results for each 365 days (The numbers in the table indicates rejection days with 10% significance level)

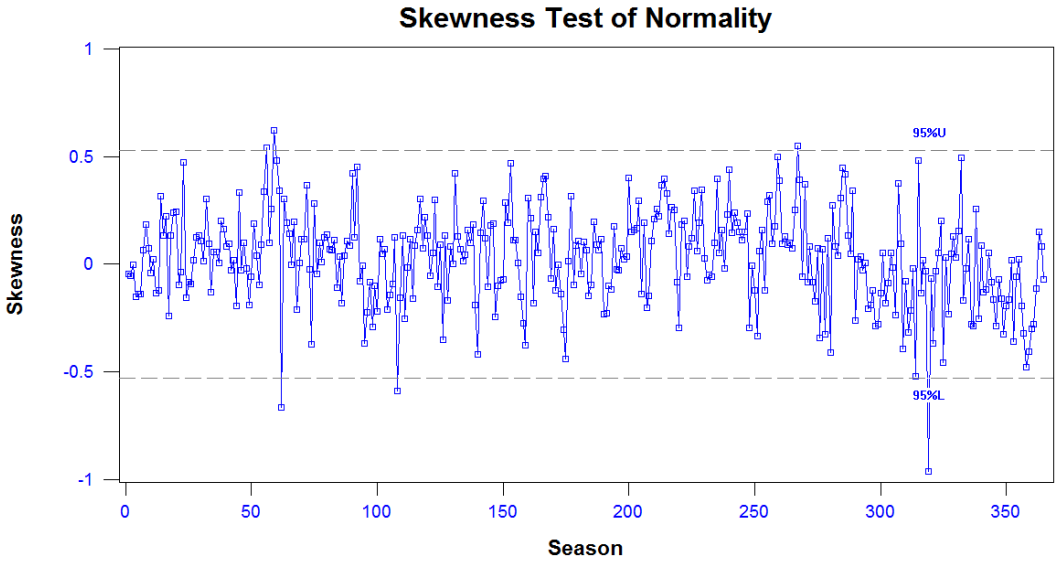


Figure 4-5 Skewness test of normality for transformed inflows

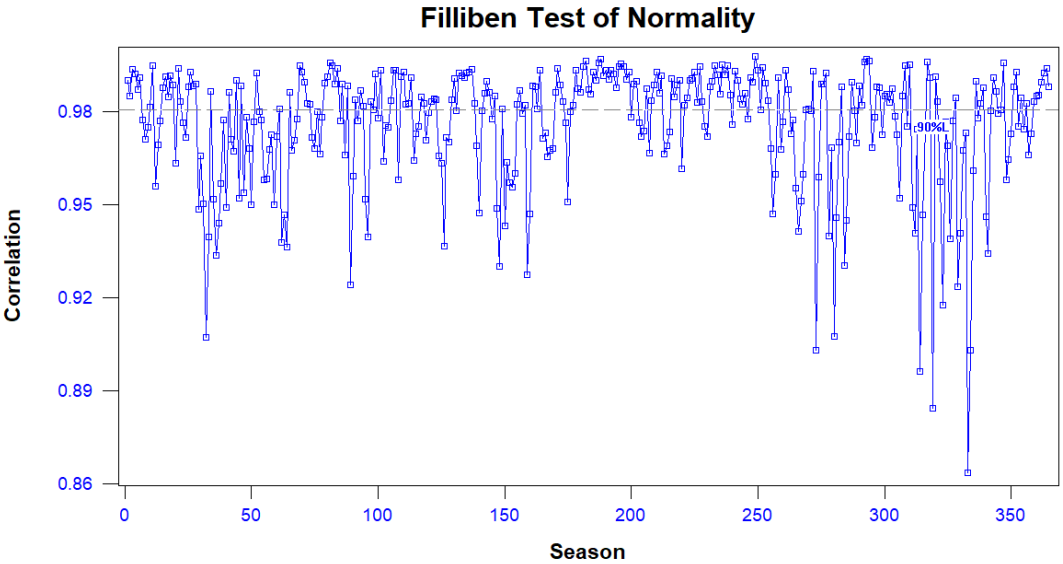


Figure 4-6 Filliben Test of normality for transformed inflows

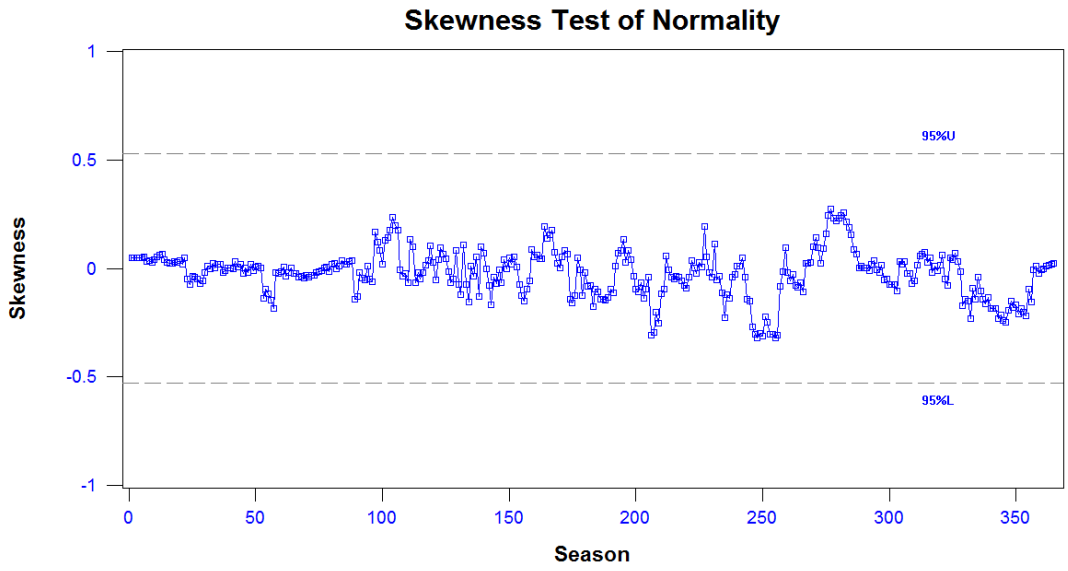


Figure 4-7 Skewness test of normality for transformed soil moisture series

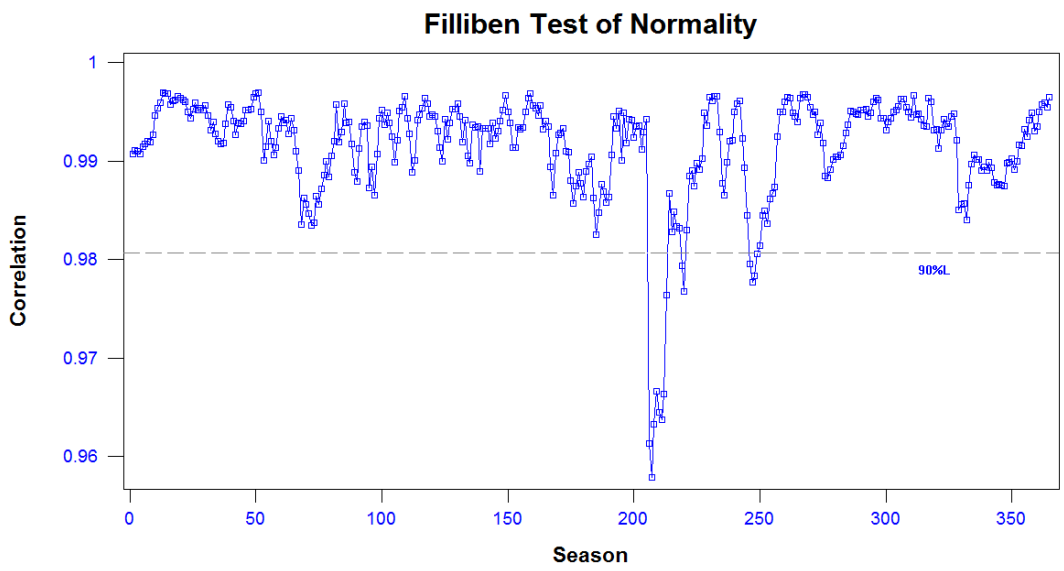


Figure 4-8 Filliben Test of normality for transformed soil moisture series

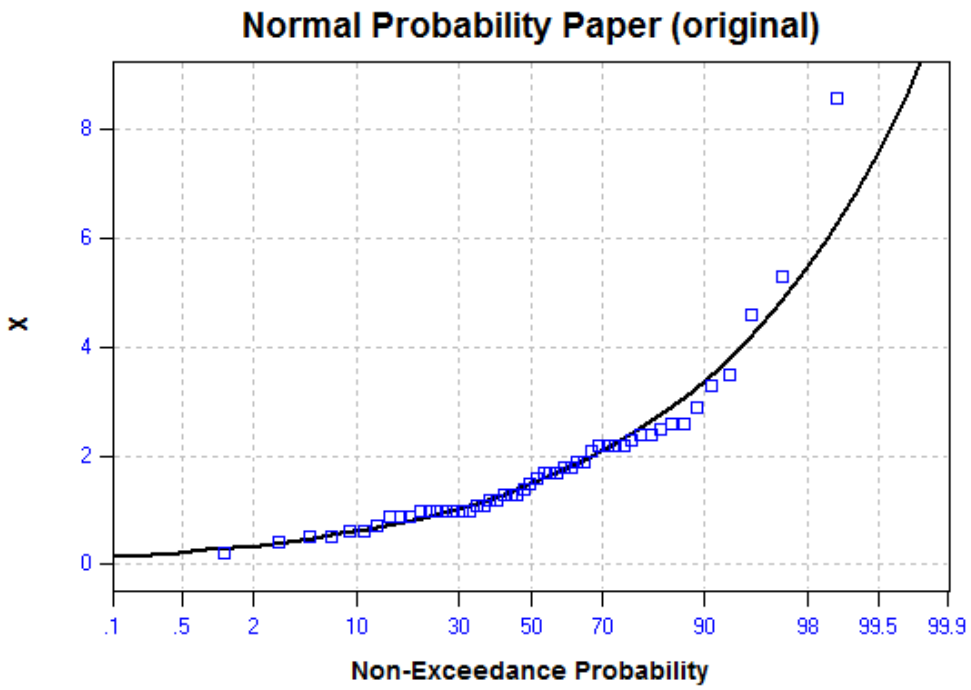


Figure 4-9 Frequency plot for inflow data, Jan 27 (original)

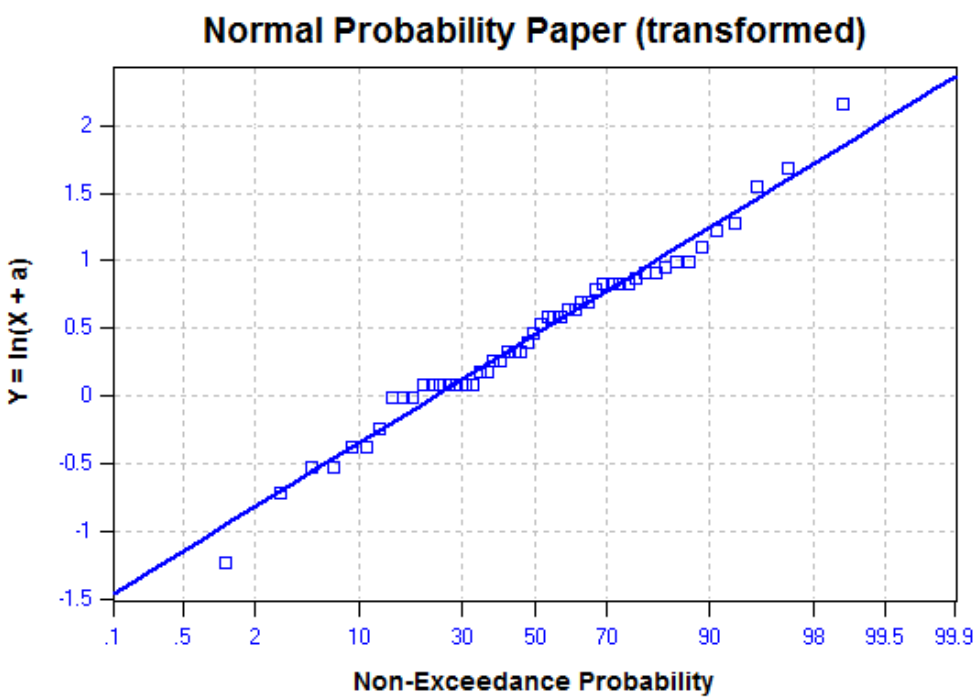


Figure 4-10 Frequency plot for inflow data, Jan 27 (transformed)

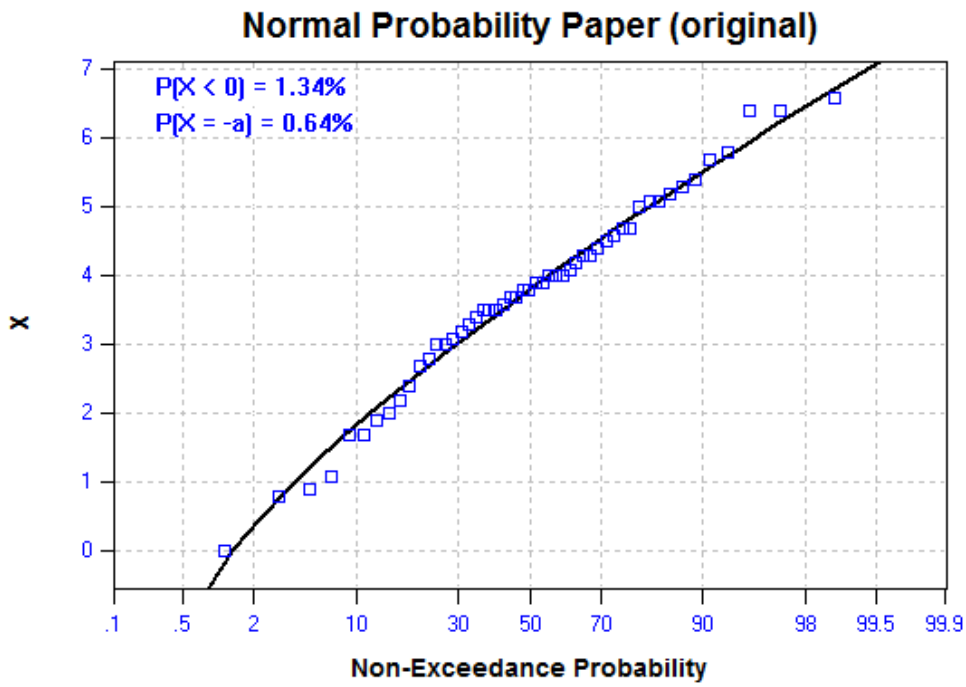


Figure 4-11 Frequency plot for soil moisture, Feb 9 (original)

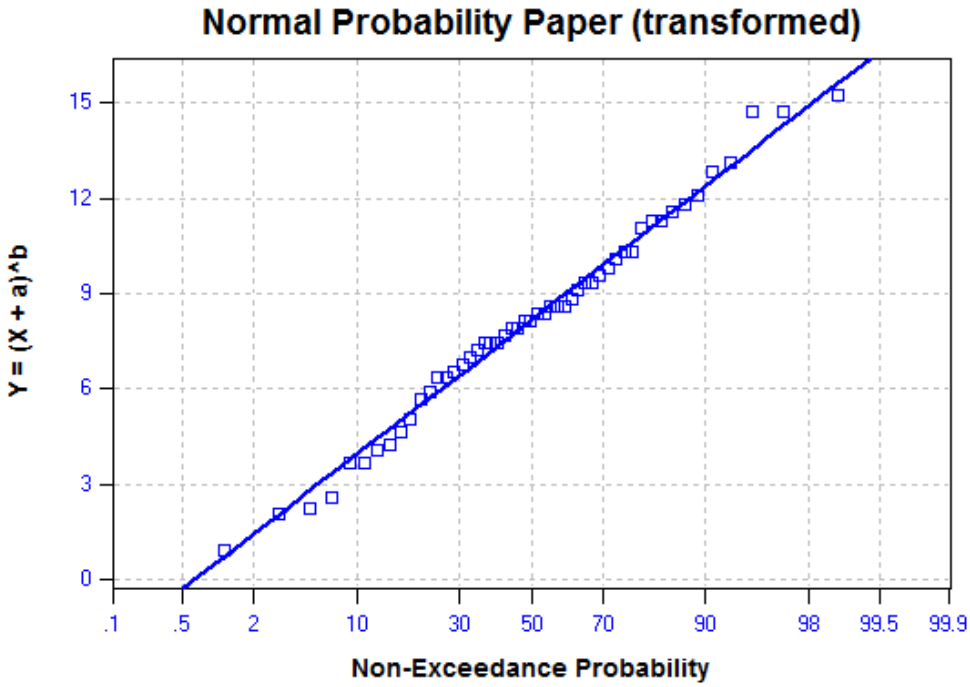


Figure 4-12 Frequency plot for soil moisure, Feb 9 (transformed)

4.2.2 Discretization of State Variables

The state variables (e.g., storage and inflows) are continuous variables. In order to describe transitions between different states in the system, these continuous variables were approximated by discretized values. This allows the use of the discrete DP recursive equation (Tejada et al. 1993).

In particular, with the assumption that inflow series are serially dependent, it is necessary to consider inflow transition probabilities. Given the discretization schemes, state transition can be represented by a transition probability matrix. Generally, it is assumed that finer intervals can increase optimization accuracy; but the number of available inflow sequences is limited, and the characteristics of inflows are not well-defined (Chen 2004; Kim and Palmer 1997).

A challenge when using DP is to choose an appropriate state resolution, keeping in mind that the finer state discretization brings additional computational burdens. A proper state approximation with suitable number of discretization is recommended to limit the required computational effort while achieving suitable accuracy (Tejada, PhD thesis, 1990).

(1) Storage

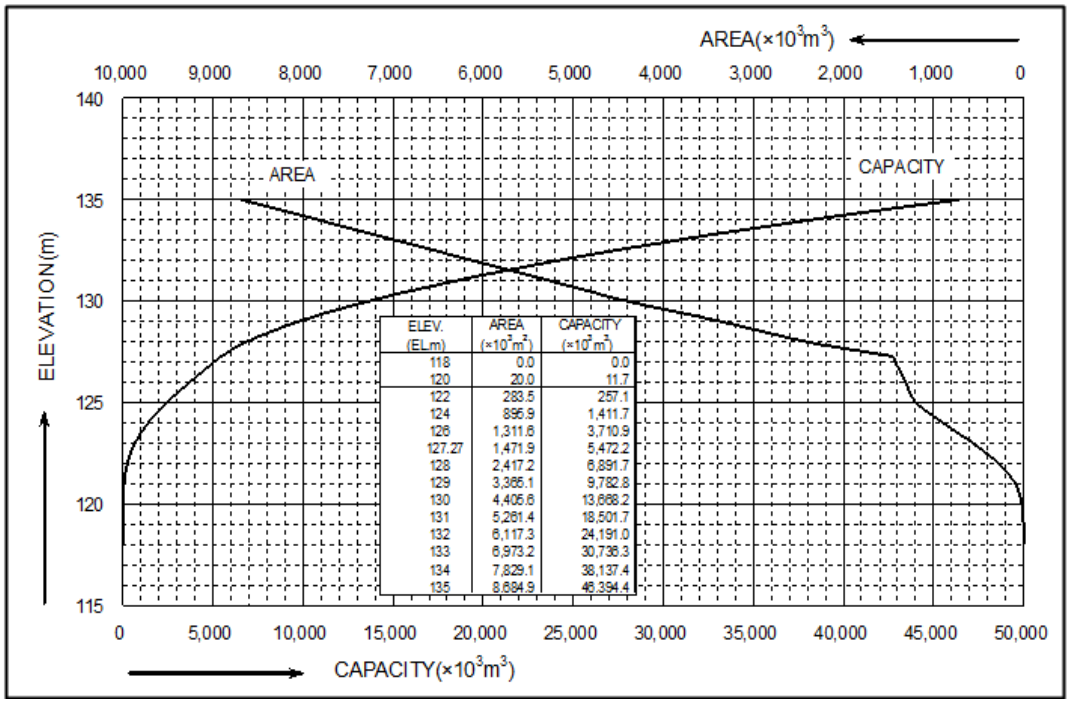
In the storage discretization, the number of required storage intervals is dependent on the characteristics of the system's reservoir, such as reservoir capacity and inflow distribution (Kim and Palmer 1997; Chen 2004). Previous studies on storage reservoir discretization (e.g., Doran 1975; Klemes 1977; Goulter and Tai, 1985; Karamouz and Houck 1987) suggested that the number of storage intervals between 7 and 50 is reasonable depending on the reservoir system features.

In general, a coarse discrete representation of the storage can adversely lead to the development of poor reservoir operation policies (Klemes 1977). Thus, choosing an

appropriate discretization method should be carefully performed to build a reasonable model (Klemes 1977; Born 1988). There are two commonly used discretization methods: Savarenskiy (1940) and Moran (1954). Savarenskiy's method suggests that the total range of storage is divided by uniform intervals from the minimum to the maximum storage with an increment Δ. In Moran's method, the last and first intervals are discretized with $\Delta/2$, and intervals in between are uniform Δ. Overall, the majority of the previous studies have adopted Savarenskiy's method, instead of Moran's, because of the following reasons.

In a research conducted by Karamouz and Houck (1987), the number of discretization levels was determined based on the ratio between annual inflows and target storage capacity. For example, the authors recommended 20 to 30 reservoir discretization storages for small and medium reservoirs (20-50% of annual inflows) and 50 or more discretization levels for larger reservoirs (capacity greater than annual inflows) (Karamouz and Houck, 1987). As the Bosunggang reservoir is classified as a small reservoir, a discretization with 20 storage levels will be adopted. Moreover, to identify consequences of the resolution of storage discretization in reservoir optimization, a coarser discretization level with only five storage levels will also be considered. Performance will also be compared between the models with 20 versus five storage levels.

To build a more reliable model, the most recent reservoir capacity survey report (KHNP, 2004) was used to account for net head and reservoir volume capacity since Bosungang HPP has been operating for over 85 years, a large volume of sediments may have accumulated which would reduce reservoir capacity, and this should be considered in the optimization model. Figure 4-13 presents characteristics of the reservoir capacity of Bosunggang HPP.



ELEV. (EL.m)	AREA (×10³m²)	CAPACITY (×10³m³)
118	0.0	0.0
120	20.0	11.7
122	283.5	257.1
124	895.9	1,411.7
126	1,311.6	3,710.9
127.27	1,471.9	5,472.2
128	2,417.2	6,891.7
129	3,365.1	9,782.8
130	4,405.6	13,668.2
131	5,261.4	18,501.7
132	6,117.3	24,191.0
133	6,973.2	30,736.3
134	7,829.1	38,137.4
135	8,684.9	46,394.4

Figure 4-13 Bosunggang HPP water level – reservoir capacity curve and surface area, 2004

To calculate the effective height using the power generation equation, storage capacity (MCM) will be transformed into water level (i.e. elevation in meters (EL.m)). The equation to calculate water level is shown in Table 4-2. This equation has been used in real-world operations with a determination success factor (R^2) of 0.99 (KHNP capacity survey report, 2004).

Interval of H (El.m)	Water level(EL.m) – Capacity(MCM) transformed formulation	Deterministic factor (R^2)
$118.0 \leq \mathrm{H} \leq 135.0$	$\mathrm{V} = 0.0144112413H^3 - 5.2035351263H^2 + 626.3739811267H - 25136.423358$	0.99964

Table 4-2 The formation of transforming reservoir capacity and water level

(2) Inflows

Inflows (Q) is one of the state variables that can be represented by a continuous distribution, and it is a main component in the SDP that is characterized by hydrologic uncertainty. To obtain reasonable results from the optimization model, continuous inflows at each stage should be discretized into appropriate intervals with certain representative values as shown in Figure 4-14.

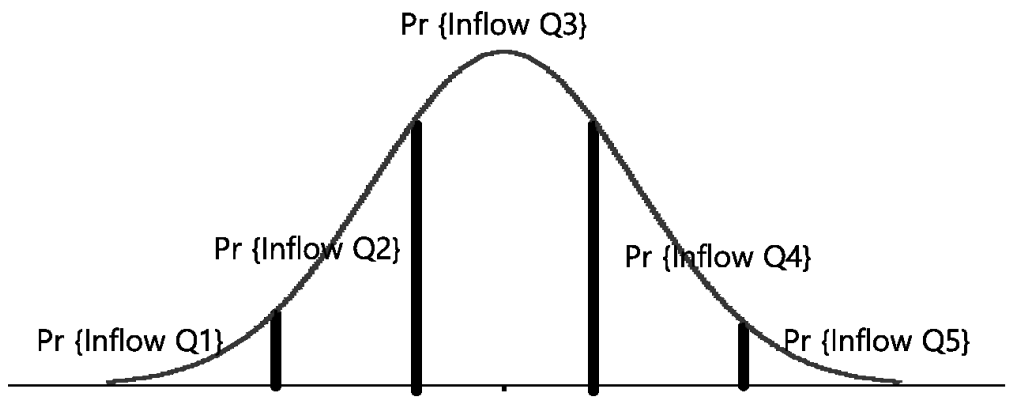


Figure 4-14 Inflow discretization and probability

Since inflow discretization involves uncertain characteristics of inflows, further work is required to better represent inflow characteristics each time. Inflows can be represented by any probability distribution; however, it is possible for extreme inflows to occur that are less than the 2% or more than the 98% quantile. If these extreme inflows are poorly represented, it could bring about problematic issues in defining accurate probability for each inflow interval (Chen 2004). Furthermore, this problem will result in poor transition probabilities that will be used to account for the state transition in SDP (Karamouz and Vasiliadis 1992; Kim and Palmer 1997).

Theoretically, it can be expected that dense discretization analysis may potentially improve model resolution; however, such approach is not practically applicable in DP optimization because of the issue of computational burden, which is proportionally

increased by the number of discretization intervals (Karamouz amd Vasiliadis 1992). In practice, given the accumulated historical inflows data, the probabilistic approach with theoretical a distribution has been widely used in hydrology to infer an expected quantile.

This probabilistic approach breaks down the whole probability section into either uniform or non-uniform schemes. Kim (1997) pointed out that a uniform scheme may overestimate the tails of the probability curve and underestimate the middle part of the probability curve. For this reason, a non-uniform scheme has been favored in SDP optimization, and will therefore be employed in this study.

The optimal discrete representative value of each interval is specified with a normal distribution. To minimize the mean squared error, a non-uniform symmetric scheme assigns the standardized characteristic flows and their associated probabilities for the normal distribution. That approach has also been applied by others to define inflow intervals (Max 1960; Pegram et al. 1991, and Tejada et al. 1993;1995). Born (1988) compared the effectiveness of using different numbers of discretization intervals on inflows and concluded that fine inflow intervals do not guarantee better performance. In addition, Pegram et al. (1991) also suggested that the five non-uniform symmetric method (Table 4-3) presented was a sensible approach with regards to computation efficiency. Therefore, this method will be used for inflows discretization in this study.

Value	-1.72	-0.76	0	0.76	1.72
Probability	0.107	0.245	0.296	0.245	0.107

Table 4-3 Characteristic values and associated probability for normal distribution, Pegram et al. (1991)

4.2.3 Optimization Formulations

In building a reservoir optimization model, essential components such as the objective function, decision variable, and constraints should be first defined. The major objective of hydropower optimization in this study is to maximize hydropower generation with an optimal policy for operations. The decision variable is the release through the powerhouse at each time step and the spill. Thus, determining the release schedule for the two discharges is the primary purpose of the hydropower optimization.

In DP optimization, the system status at each time step can be represented by state variables (e.g., storage and inflows) and each of them can be defined in different ways based on the system characteristics and the purpose of optimization.

In this study, to recognize variability under a wide range of SDP and SSDP recursive formulations, four different recursive formulations were adopted, which have been successfully applied in previous studies (Stedinger et al. 1984; Tejada et al. 1990; Tejada et al. 1995; Kelman et al.1990; Côté et al. 2011).

Specifically, the soil moisture series generated by SSARR will be evaluated for its use as a hydrologic state variable in the SDP_H_S optimization equations (4-3). In the step of implementing optimization, each backward recursive equation will be executed with a daily time step from the last day of the year (Dec 31) to the first day of the year (Jan 1) over one year. This computation will be repeated over the successive one-year horizon, and terminated once steady state is reached, that is, the optimal policy has been achieved for the formulated model.

(1) SDP_N (Stochastic Dynamic Programming without hydrologic state variable)

$$f_t(s_t) = \underset{q_t}{E}\left(\max_{u_t}\{B_t(s_t, u_t, q_t) + f_{t+1}(s_{t+1})\}\right) \quad (4\text{-}2)$$

$$\forall s_{t,} u_{t,} q_t, t \in \{1,2, \dots, T\}$$

Where: B: $benefit\ function$

s: $storage(m^3)$

q : $inflow\ to\ the\ reservoir(m^3/s)$

u : $water\ through\ the\ power\ house\ turbine(m^3/s)$

h : $hydrologic\ state\ variable$, *soil moisture*

f_{t+1}: $future\ value\ function$

t: $time\ step, 1\ day$

T: $time\ horizon, 1\ year$

In this model, although the inflow uncertainty is considered with unconditional probability of q_t, hydrologic persistence in subsequent stages is neglected. That is, inflows at consecutive stages are fully independent without any correlation between successive inflows. This model can be regarded as the most naïve model in this study.

(2) SDP_H_S (Stochastic Dynamic Programming with soil moisture)

$$f_{t,}(s_{t,} h_t) = \underset{(q_t|h_t)}{E}\left(\max_{u_t}\left\{B_t(s_t, u_t, q_t) + \underset{(h_{t+1}|q_t, h_t)}{E}\left[f_{t+1}(s_{t+1,} h_{t+1})\right]\right\}\right) \quad (4\text{-}3)$$

$$\forall s_{t,} q_t, h_t, t \in \{1,2, \dots, T\}$$

h : $hydrologic\ state\ variable$, *soil moisture*

Here, SDP_H_S, Equation (4-3) is a more sophisticated model in comparison to SDP_N because it recognizes hydrologic persistence by including additional state variables. States of system in this formulation are discretized storages, inflow and hydrologic state variables, and the transition from state to state at each time step in the system were represented by transition probabilities.

Simple and multiple regressions were used to calculate the transition probability (Born 1988; Kelman 1990; Tejada et al. 1995; Faber and Stedinger 2001; Kim et al. 2007; Côté et al. 2011). Inner expectation of future forecast variable, h_{t+1} was conditioned by both representative values of each interval, q_t and h_t. To calculate both inner and outer expectation values, two types of transition probability matrix were generated by simple and multiple regressions (Born 1988; Desreumaux 2014) a priori on a daily-basis.

(3) SDP_H_Q (Stochastic Dynamic Programming with current inflows)

$$f_{t,}(s_{t,}q_t) = \max_{u_t}\left\{B_t(s_t, u_t, q_t) + \underset{(q_{t+1}|q_t)}{E}\left[f_{t+1}(s_{t+1,}q_{t+1})\right]\right\} \qquad (4\text{-}4)$$

$$\forall s_{t,}q_t, h_t, t \in \{1,2,\dots,T\}$$

The hydrologic state variable most commonly used were current flow q and the previous q_{t-1} (Alarcon and Marks, 1979; Loucks et al. 1981, Tejada et al. 1993). This study assumed that the current period's flows are known, so Equation (4-4) model was compared with output of SDP_H_S.

(4) SSDP_N (Sample Stochastic Dynamic programming)

SSDP model with historical scenarios is a similar model that was compared with SDP. SDP uses a recursive equation to evaluate and identify good decisions and to update the future value function. SSDP uses one equation to identify good decisions, and separate equation to update the future value function (Faber and Stedinger 2001; Kim et al. 2007). Previous research found that SSDP generally performs better than SDP due to its capability of accounting for the temporal and spatial aspects of hydrology by adopting inflows scenarios as the basis for the optimization, instead of using discretized probability distribution of inflows (Kelman et al.1990; Faber and Stedinger 2001; Kim et al. 2011). Kelman et al. (1990) proposed the SSDP model for which the probability for each of the scenarios to actually occur is equivalent to 1/M, where M equals the number of different historical scenarios that are considered (Faber and Stedinger 2001; Lamontagne 2015). The SSDP formulation used in this study is:

$$\max_{u} \left[B_t(s_t, q_t(i), u_t) + \frac{1}{M} \sum_{i=1}^{M} f_{t+1}(s_{t+1,}\, \mathrm{i}) \right] \tag{4-5}$$

$$\forall\, s_t, i \; and \; t \; \in \{1, \dots, T\}$$

$$f_{t,}(s_{t,} i) = \left[B_t(s_t, q_t(i), u_t) + f_{t+1}(s_{t+1,}\, i) \right] \tag{4-6}$$

$$\forall\, s_t, i \; and \; t \; \in \{1, \dots, T\}$$

M: *number of historical scenarios*

i: index for stream flow scenarios

$q(i)$: *stream flow in from scenario i*

The two SSDP equations appear above; Equation (4-5) can be considered as a decision model that identifies an optimal release to maximize the sum of the current benefits and future benefits in each stage subject to inflow uncertainty. After optimal

turbine release, u_t, is determined with Equation (4-5), Equation (4-6) then updates for each scenario the future value function. Equation (4-5) correspond to operations without using forecast information.

4.2.4 Transition Probability

Inflows in SDP, although generally described by a continuous distribution, need to be discretized at each stage. To account for persistence between consecutive inflows, a transition probability is specified in order to calculate the expectation terms.
With the aim of describing transition probability more effectively, Stedinger et al. (1984) introduced a way to generate transition probability that can reasonably account for inflows persistence by using the best forecast method. Later, the Bayes Theorem was successfully included in the SDP and SSDP optimization in order to consider forecast uncertainties by using forecast information updated with current hydrology conditions (Karamouz and Vasiliadis 1992; Kim and Palmer 1997; Faber and Stedinger 2001; Haguma et al. 2014; Lamontagne 2015).

In Equation (4-3), both inner and outer expectations are represented with different transition probabilities. The outer expectation is the probability of transitioning from the current forecast, h_t to current period inflow, q_t, the second is the transition probability of succeeding forecast, h_{t+1} given current inflow q_t and hydrologic variable h_t. The simple and multiple linear regression methods were carried out to build the transition probability matrix, as seen in previous studies (e.g., Born 1988; Faber and Stedinger 2001; Côté et al. 2011; Desreumaux et al. 2014; Côté and Leconte 2016). To calculate the transition probabilities, it is assumed that there is a linear relationship between the forecast variable and future inflows, inflows, or their logarithm. In Table 4-4, ε_t represents the residuals of the least square fitting method, which is normally distributed with $\mathrm{E}[\varepsilon] = 0, Var[\varepsilon]=\sigma^2$.

The value of the conditional probability for state interval transition is obtained through the calculation for normally distributed residuals from the standard normal distribution table. Two types of transition probabilities were calculated using a linear function to account for hydrologic persistence in successive days). This transition probability was included in the SDP formulation to calculate the expectation term in equation in (4-3) and (4-4).

(1) $Q_t \mid H_t$	(2) $H_{t+1} \mid Q_t, H_t$
$Q_t = \alpha_0 + \alpha_1 \cdot H_t + \varepsilon_t$	$H_{t+1} = \beta_0 + \beta_1 \cdot Q_1 + \beta_2 \cdot H_1 + \varepsilon_t$

Table 4-4 Transition probability

4.2.5 Model constraints and benefit function

In order to honor system constraints, system features need to be represented in the optimization procedure in mathematical terms (Kim et al. 2007). The following constraints are employed with all formulations of the difference model Equations (4-2) to (4-6).

$s_{t+1} = s_t + q_t - u_t - v_t \;\; \forall t = 1,2,\dots,\mathrm{T}$
(if $s_{t+1} < s_{min}$, $u_t = s_t + q_t - s_{min} - v_{min}$, if $s_{t+1} > s_{max}$, $u_t = s_t + q_t - s_{max} - u_{max}$)

$u_t \leqq u_t^{max} \quad \forall t = 1,2,\dots,\mathrm{T}$

$s_t^{min} \leqq s_t \leqq s_t^{max} \; \forall t = 1,2,\dots,T$

$v_t^{min} \leqq v_t \; \forall t = 1,2,\dots,T$

Where: t: time step, daily
B: $Benefit\ function$, *power generation (KW)*
u_t: $Water\ through\ the\ power\ house\ turbine(m^3/s)$
h_t: $Hydrologic\ state\ variable$, *soil moisture*
v_t: $Spillage\ to\ downsteam(m^3/s)$
v_t^{min}: $Minimum\ environmental\ flow(m^3/s)$
p_t: $Power\ generation(KW)$
q_t: $Inflow\ to\ the\ reservoir(m^3/s)$, s_t: $Storage(m^3)$

In this study, the primary constraint is to meet the legally required minimum environmental flow. Thus, minimum environmental flow is allocated first since it is an underlying constraint. Then the downstream release to the two turbines is allocated to generate power. In case the future storage (s_{t+1}) is beyond the maximum reservoir capacity (s_{max}), then excess water beyond turbine capacity will be spilled through the gate. Therefore, the turbine and spill gates can work simultaneously. Values for constants describing the constraints are presented in Table 4-5.

Constraints	Value
Max. Storage (MCM)	4.7
Min. Storage (MCM)	1.0
Minimum Environmental flow (CMS)	0.47
Maximum turbine release capacity (CMS)	6.4
Maximum turbine capacity (MW)	4.5

Table 4-5 Value of constraints

The expected benefit (*B*), as measured by power (KW), is computed by using the following power generation equation (4-7).

$$P\,(h_{n,}u_t) = g \times u_t \times h_n \times \eta \qquad (4\text{-}7)$$

Where, g: Gravitational acceleration (m/sec^2)

u: the water inflow into the turbine (m^3)

h_n: net water head, forebay elevation, h (s_t, s_{t+1}) – tailrace elevation (El.m)

η: Turbine-Penstock efficiency

t: time step

4.2.6 Inclusion of hydrologic state variable

One concern is the effectiveness on forecasting in reservoir operation. Two different forecasting methods were evaluated in this study: 1) estimated soil moisture levels generated using hydrologic model, SSARR, and 2) lag-1 current inflows. It can

be assumed that the knowledge of soil moisture can be used to condition the distribution of future stream flows and improve reservoir operations (Côté et al. 2011).

The next research question is how could forecast quality have impacts on reservoir optimization when forecast variables are state variables. Lamontagne and Stedinger (2017) examined the suitability of using forecast variables, and concluded that reliable optimization performance can be achieved when there is strong correlation between forecast resources and future inflows. In this study, future successive day inflows can be better explained by previous day's inflows ($R^2 = 0.3$) than by soil moisture ($R^2 = 0.1$) based on the R^2 value. There was not a strong linear relationship between soil moisture of the previous day and inflows in the following day. This lack of a strong relationship may be due to other factors driving instream flow patterns, such as return inflows and groundwater influencing short-term future inflows. Stronger relationships were clearly observed in other studies (Stedinger et al. 1984; Côté et al. 2011; Desreumaux et al. 2014). These could be due to the fact that other researchers employed seasonal forecast with monthly time steps. In other words, taking proper forecast time into account could be a reliable and suitable means to gain the benefits of forecast techniques.

In this study, before introducing soil moisture as a hydrologic state variable, the hypothetical assumption was initially made: the soil moisture at one day prior has a linear influence on the inflows in the following day. Unfortunately, based on the forecast performance of soil moisture ($R^2 = 0.1$), this assumption turned out to be of little use in practice. But, even if the aforementioned assumption is not applicable to the actual system behavior, the major goal of this study focuses on discovering the effectiveness of SDP and SSDP optimization methods under different optimization schemes compared to the existing hydropower operation. Moreover, the present study is the first

to make use of soil moisture for SDP in Korean hydropower system. Hence, this study will be meaningful to prove the importance of introducing proper hydrologic state variable with adequate forecast lead time into SDP optimization.

4.3 Optimization and Simulation

4.3.1 Computation of Future Value Function

Identification of SDP and SSDP decision rules requires computation of the future value functions. To compute the value of the future value function at each stage, using Equation 4-1, 4-2 or 4-3, one starts with the last stage and works backward to the first stage over a fixed time period, or a repeated horizon time (e.g., one year) until a steady state is reached: the optimal policy may become constant at any stage, and then the recursive computation can stop (Loucks and Falkson 1970; Faber 1990).

The ultimate outcome of optimization in this study is to generate an optimal turbine release policy (Figure 4-15). The policy will depend upon a description of the system state (e.g., storage level and hydrologic state variable) and sequential turbine release that is aimed to maximize optimization objectives.

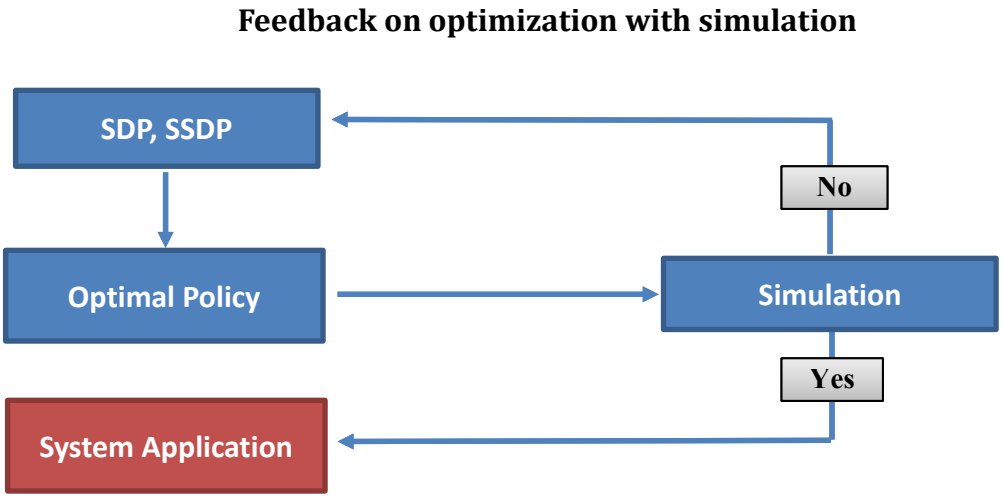


Figure 4-15 Optimziation feed back with simulation, (Ahmad et al. 2014, Fig2. P3397)

4.3.2 Simulation

Another step in Figure 4-15 is to validate the developed optimization model to see if it works properly under and captures real system dynamics and constraints. A common strategy to validate a developed optimization model is to couple the model with simulations as shown in Figure 4-15. In such simulation, performance criteria can include both the average annual power capacity and the average annual downstream spills. Furthermore, performance of each suggested optimization policy in the real system will be evaluated and compared under actual hydropower plant schemes including the actual operation record in 2016.

For the simulations, the initial storage is specified as 4.5 MCM, which is the maximum effective storage. The period of historical data used to develop an optimal policy extends from 1965 to 2015, a total of 51 years of record and our 2016 for simulation. To evaluate model behavior under wide range of inflows characteristics (e.g., extreme high and low flows), one can use historical inflows available or synthetic generated inflows for simulation. However, aim of this study is to suggest a desirable optimal release policy under the newly established legal environmental flows that was implemented in the beginning of 2016. Although, this one-year simulation is statistically limited, it allows a simple comparison with actual 2016 system Bosunggang HPP system operation.

The adopted time step in the case study is daily. In general, for both operators and water managers in the real world, a common time step is daily because of its distinguished merit of instantly adapting to changeable system behavior and also making use of reliable short-term inflow forecast (Pérez-Díaz and Wilhelmi 2010; Fan et al. 2016).

The computation of the future value function also produces policy tables that can be used to operate the turbines using the system state variable (e.g., storage). However, due to the approximation of system state variables with discretization approach, in practice, the actual system state (red cross symbol) is typically not a pre-defined system of storage states (blue filled circle) in Figure 4-16.

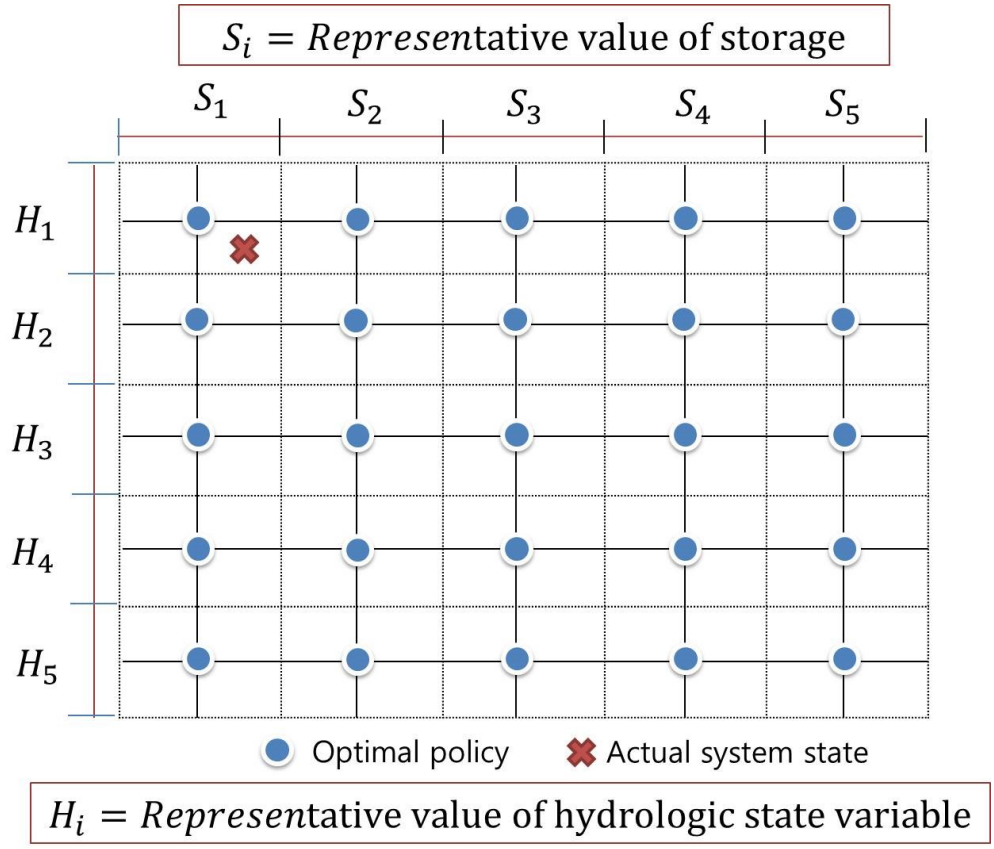


Figure 4-16 Optimal decision policy with discretized state variables, Chen 2004

To obtain the true future value function value for any state of interest, interpolation was employed. Similarly, state variables derived from SSDP also suffer deviations in representing the actual system condition. The resulting SSDP optimal policy is generally derived based on historical scenarios; however, in actual operations there is no guarantee that identical scenarios will take place in real time operation.

Hence, to address the above issue, either the interpolation or the re-optimization methods were commonly adopted in implementing of established optimal policy at the simulation step (Tejada et al. 1993; Faber and Stedinger 2001). In this case study, the re-optimization method is employed in the simulation with the aim of obtaining good decisions by using the derived future value function with the current system conditions.

Rule Curve

In an actual system, it is generally acceptable practice for this reservoir to be operated based on a simple rule curve. In this study, the rule curve and associated equations are provided below. Rule curve operation will be compared with SDP and SSDP optimization results.

Here we employ a possible rule curve that generates as much power as is feasible.

1) Determine if a spill is necessary ($Spill_t$)

$$if\ S_t + Q_t - U_{max} - EF\ >\ S_{max}\ ,\ Spill_t = S_t + Q_t - U_{max} - S_{max}$$

$$else,\ Spill_t = EF$$

2) Compute turbine release (U_t) as maximum possible value

$$U_t = \min(S_t + Q_t - Spill_t - S_{min}, U_{max})$$

3) Compute final storage (S_{t+1})

$$S_{t+1} = S_{t+1} + Q_t\ -\ Spill_t -\ U_t$$

Where

EF: *Minimum environmental flows*

U_{max}: *Maximum turbine release*

U_t: *Turbine release,*

S_t: *Storage*

Q_t: *Inflows*

$Spill_t$: *Spill including EF*

Simulation Results

Verification of a simulation model is generally achieved by comparison of the model outputs to actual records. The actual turbine capacity (R=6.4CMS) is based on real-system configurations. So, it is assumed that if the simulation model is accurate, its performance should match actual operation in straightforward situations. Actual operation reservoir spillage (m^3/s) records were compared to outcomes derived by SDP_N in Equation (4-2). The occur actual spill (green line) is likely to be similar with model's simulation (red line) (Figure 4-17).

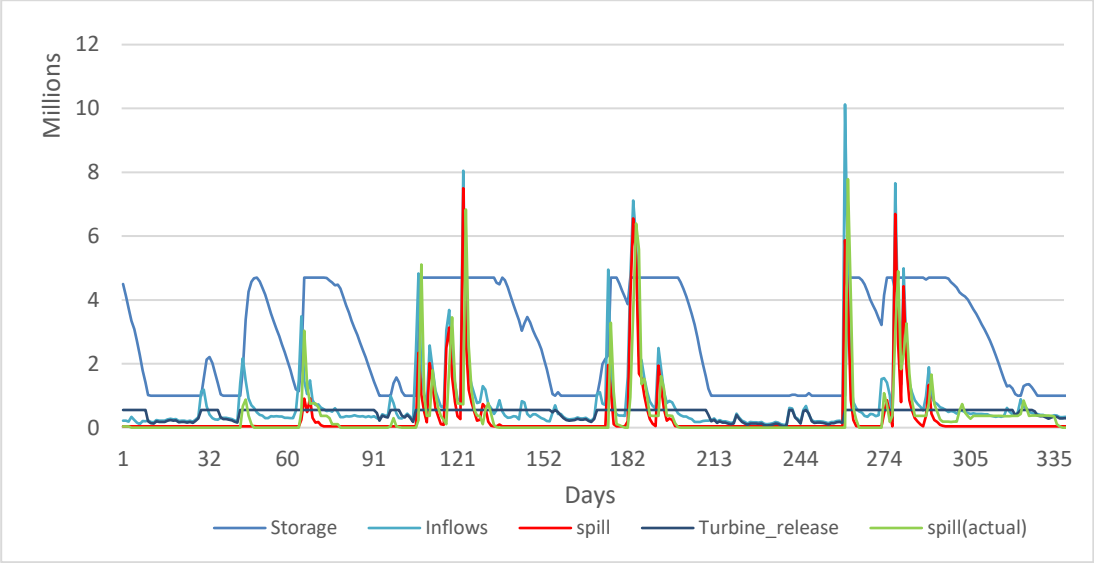


Figure 4-17 Simulation result with actual spill for 2016 (SDP_N)

In the simulation result, the mass balance in reservoir, maximum reservoir storage (S_{max}) and, minimum storage (S_{min}) are checked if it violates the above defined constraints. For the simulation, re-optimization method was used by referring to future value function stored in the optimal policy.

4.3.3 Comparison of Rule Curve and Optimization Model Policies

There are 5 models that whose performance will be compared with historical operation:

- Rule curve: operation reservoir with a target storage level, 4.5 MCM
- SDP_N: SDP model without hydrologic state variable
- SDP_H_S: SDP model with hydrologic state variable, soil moisture
- SDP_H_Q: SDP model with hydrologic state variable, lag-1 inflows
- SSDP_N: SSDP model without persistence

The performance of the four models were compared with both the actual historical releases in 2016 and the predicated release using the rule curve for the Bosunggang Hydropower Dam. Performance was evaluated using two metrics: power generation and spillage.

(1) Power Performance

Figure 4-18 and Table 4-6 show simulation results for power generation with the rule curve, SDP, and SSDP models.

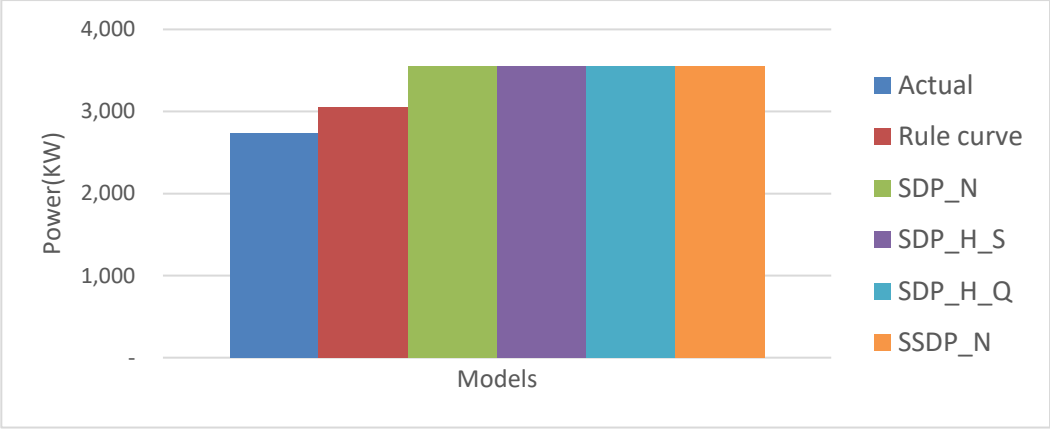


Figure 4-18 Annual average power output for 2016 inflows

(unit: KW)

2016 (Actual)	Rule curve	SDP_N	SDP_H_S	SDP_H_Q	SSDP_N
2,735	3,047	3,558	3,558	3,558	3,558

Table 4-6 Annual average power output for 2016 inflows

Overall power generation increased by 30% for all optimization models as compared to the actual power generation reported in the historical records of 2016. In addition, about 17% of additional power production were obtained by applying any of the optimization methods as compared to a simple rule curve operation. However, there was no difference in performance among the four different optimization models.

(2) Reduced spillage

Figure 4-19 reports the annual average spillage. Spillage to downstream from reservoir, a secondary performance standard, is substantially reduced in the suggested optimization models in comparison to the actual spillage records in 2016.

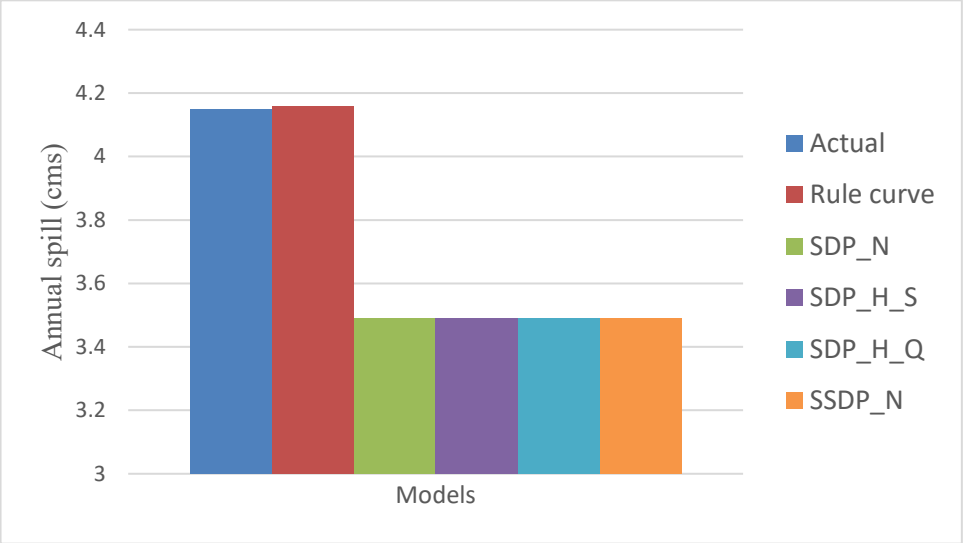


Figure 4-19 Annual average downstream spill for 2016 inflows

(unit: m^3/sec)

2016 (Actual)	Rule curve	SDP_N	SDP_H_S	SDP_H_Q	SSDP_N
4.15	4.16	3.49	3.49	3.49	3.49

Table 4-7 Annual average downstream spill for 2016 inflows

The Bosuggang HPP system has a small reservoir. The water in the reservoir can be regarded as a potential resource for future hydropower generation. In contrast, spillage releases without power generation can be regarded as losing potential energy without gaining the appropriate energy benefit, unless the spill is an environmental release. As such, reduction of spillage can be used as an alternative metric to power output for evaluating the four models. For this reason, an effective reservoir operation policy is required to take advantage of the available water impounded in reservoir, which will in turn reduce non-profitable spills.

Such reduction is because the optimal policies release water for only minimum environmental flow unless necessary spillage takes place when the present storage exceeds the maximum storage due to excessive inflow. Hence, the model will keep storing water to the reservoir that can be a power generation source by reducing the unnecessary spillage.

(3) Increased ecological constraint

The present minimum environmental flow requirement of 0.47 CMS could be increased at some point in time due to either a modified downstream habitat or to a new regulation that requires more releases downstream. Increasing the minimum flow value could be another concern for the hydropower agency because the amount of power production would likely be reduced in comparison to the actual performance with current ecological constraint, even under the optimal operation. To evaluate this issue, the SDP_N model was rerun with five different environmental constraint values, progressively increasing the minimum environmental flows from 1 CMS to 3 CMS keeping all other parameters the same.

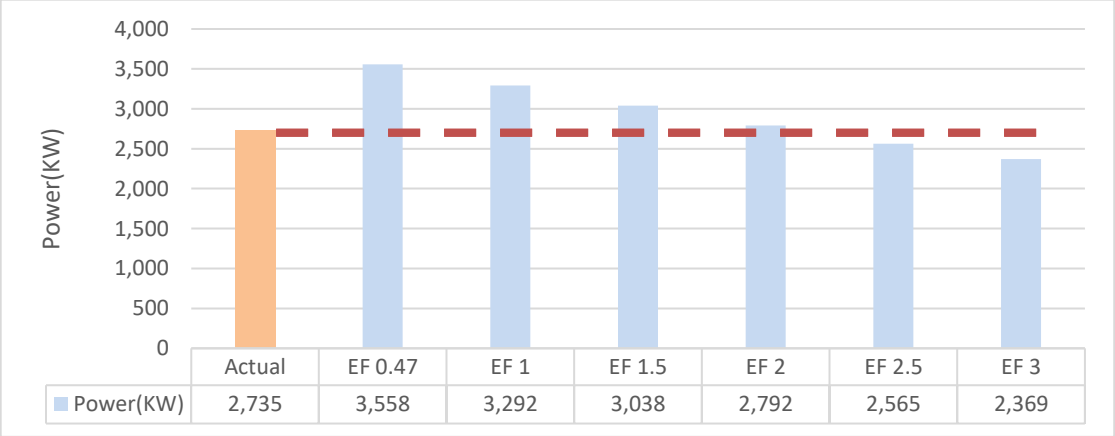


Figure 4-20 Power generation under different minimum environmental flows for 2016 inflows

Under the additional spillage obligation to meet such increased ecological constraint, SDP_N is capable of covering the increased environmental flow up to 2CMS as the same level with the existing amount of power production as shown in Figure 4-20. This case study considers how annual power production will change should more demanding ecological constraints be imposed, even under optimized hydropower operation. As anticipated, due to the increased minimum environmental flows, power production decreases linearly with each increase in the required environmental flows.

4.4 Summary

A suite of four different optimization models were created to determine whether power output and spillage losses are being impacted by the requirement of a minimum environmental flow requirement recently implemented on the Bosungaang HPP in Korea. The ecological constraint, e.g. a minimum environmental flow, was successfully added to optimization models using SDP and SSDP frameworks. Greater annual power production and smaller annual spill were achieved by all of the policies generated by the optimization models in comparison to the historical operation decisions. In addition, when proposed minimum environmental flows were increased, hydropower optimization can compensate for lost production over historical operation up to a maximum required release of 2 CMS. Therefore, as a non-direct approach suggested, SDP and SSDP can mitigate the consequences of environmental flows in Bosunggang HPP operation.

In reality, Bosunggang HPP has a single purpose of generating hydropower, and it drives the optimization as the single term in the objective function with small turbine capacity. The supplementary work can be possibly carried out in case of introducing additional objective in existing reservoir such as flood control, water supply, and even recreational purposes. In next chapter 5, the actual system will be modified to see how suggested different SDP and SSDP model behave under different optimization schemes.

CHAPTER 5 SYSTEM MODIFICATION

The optimal release decisions for the current, actual Bosunggang HPP system, with several small turbines, is rather obvious and was implement as the "rule curve". The optimal policy is to generate power at the maximum level possible level in each time period, emptying the reservoir if necessary. There was no penalty for not meeting the environmental release, so there is not penalty for emptying the reservoir; However, the environmental. flows were so small, having insufficient inflow to meet them was not a problem. Similarly head effects had little or no impact on energy generation, so it was not necessary to keep a minimum pool to support a minimum head for power generation. For these reasons, characteristics of each suggested optimization model were not fully evaluated in chapter 4.

One can assume, however, that the existing hydropower system configuration could be modified with different parameters and the SDP and SSDP models were used to investigate the system behavior in response to the following system conditions:

1) installing additional turbines to enhance power generation capacity or an expanded reservoir to have larger storage capacity,

2) introducing additional reservoir objectives with penalty term (i.e., navigation),

3) resolution of the state variable

In this chapter, several modifications to the actual system were carried out, and examined in relation to behavior suggested optimizations, SDP and SSDP.

5.1 Optimization Model Performance for Different Situations

5.1.1 System Configuration

Lamontagne (2015) introduced the concept of dimensionless diagnostic metrics to describe system characteristics based on reservoir capacity and mean inflows. This concept provided some sense of dealing with relationship among desire time step for analysis, volume, and turbine capacity among a wide arrange of hydropower system configuration. For the present case study system, the reservoir storage capacity is 4.7 (MCM), maximum turbine release is 6.4(㎥/s), and the average daily inflow (1965~2016yr) is 9.1 ㎥/s. V_a: reservoir active storage, u_{day}: $average\ daily\ inflow$, V_{PH}: volume of water through the turbine. Table 5-1 reports the diagnostic metrics of Bosunggang HPP: the time to empty the reservoir without any inflows is 8.5 days, which is rather short. The time required to fill the storage to capacity with average flows and no releases is 6.0 days. That is even shorter. In reality, only small releases can go through the existing turbines. only small releases can go through the existing turbines. However, in reality, the system structure is not fixed as larger turbines could be installed. Therefore, it can be anticipated that suggested optimization models' performance could be varied under different system configurations.

Formula	$PH_{days} = V_a/V_{PH}$	$ST_{days} = V_a/u_{day}$
Value	8.5 $days$	6.0 $days$

Table 5-1 system characteristic metrics

With the aim of accounting for possible variations in system configurations, this study addressed different turbine capacities for a fixed hydrology and reservoir storage capacity.

Figure 5-1 reports results with different turbine capacities for a large storage reservoir with a volume of 10MCM.

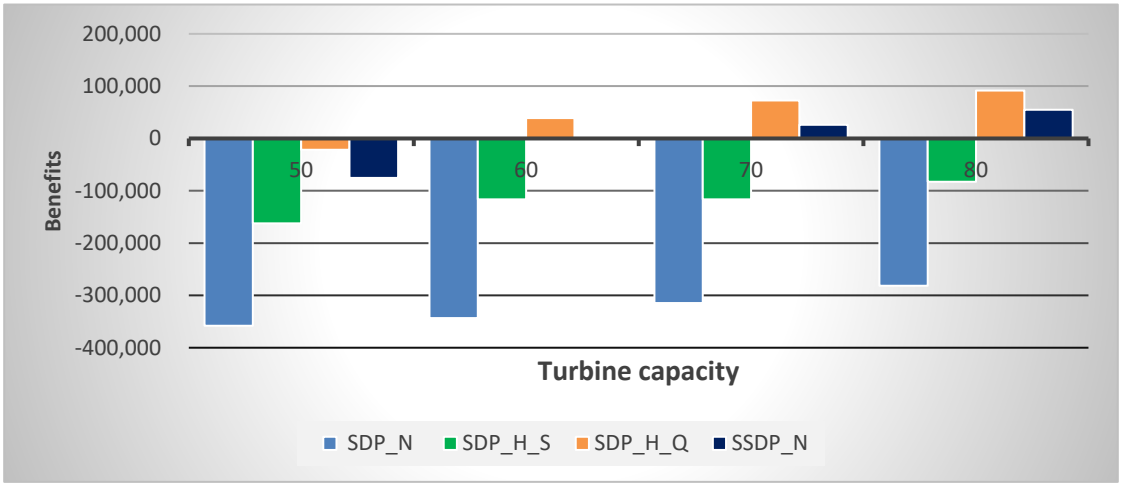


Figure 5-1 Result under turbine scaling for large storage (10MCM) using 2016 inflows

	50cms	60cms	70cms	80cms
SDP_N	-357,863	-343,305	-314,380	-281,595
SDP_H_S	-162,432	-116,161	-116,151	-82,471
SDP_H_Q	-21,561	39,042	72,755	91,803
SSDP_N	-75,442	-2,114	26,320	54,772

Table 5-2 Result under turbine scaling for large storage (10MCM) using 2016 inflows

Results show that benefit linearly increase as turbine capacity increase. The SDP_N shows poor performance, and SDP_Q shows highest performance among all sugested models. The better model is good at avoiding negative penalty from keeping target water water level.

5.1.2 Additional System Objective

The original benefit function was solely calculated by power production (KW) term to maximize the benefit. A minimum flow was then added. Although this can make optimization problems simple, discovering the characteristics of each suggested model can be restricted. Therefore, the original benefit function for actual system was revised by adding a penalty term on deviation from certain target reservoir volume. This additional analysis can be useful when reservoir in hydropower can be used for additional objectives such as recreational purpose, water supply and flood control. The modified benefit function is

$$\mathrm{B} = \mathrm{P}(u_t, h_t(s_t, s_{t+1})) \times \mathrm{p} - |(\mathrm{TWL} - s_{t+1})| \times \mathrm{c} \tag{5-1}$$

Where, u_t: $turbine\ release\ (m^3/s)$

P: $power\ production\ (kw)$

s_t: $storage\ at\ t\ (m^3)$

s_{t+1}: $storage\ at\ t+1\ (m^3)$

TWL: $target\ reservoir\ volume\ (m^3)$

p: $benefit\ per\ kw,$

c: $penalty\ coeffcient$

Figure 5-2 reported the results with different penalty for small storage, 5MCM.

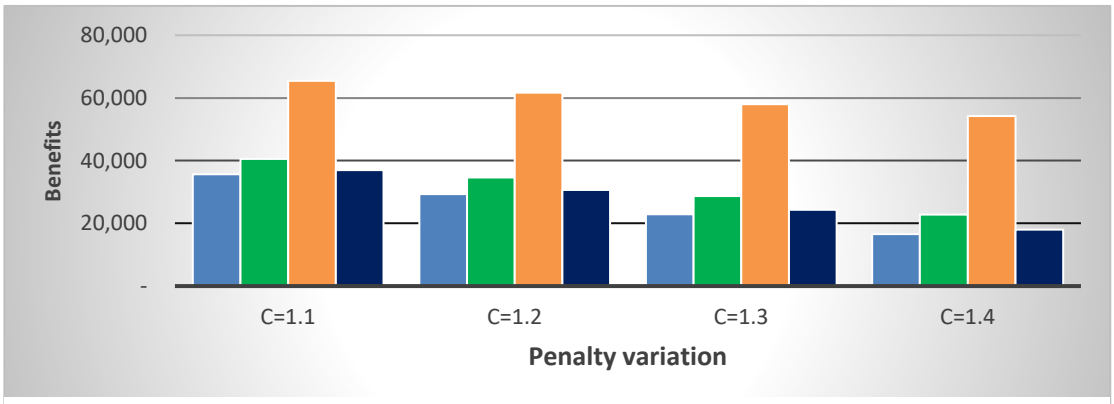


Figure 5-2 Result under penalty variation for small storage (5MCM) for 2016 inflows

	1.1	1.2	1.3	1.4
SDP_N	35,670	29,296	22,921	16,547
SDP_H_S	40,602	34,665	28,728	22,790
SDP_H_Q	65,473	61,736	57,998	54,261
SSDP_N	36,942	30,642	24,343	18,044

Table 5-3 Result under penalty variation for small storage (5MCM) using 2016 inflows

Total benefit decreased with an increasing penalty coefficient for each model. The pattern of benefits obtained by the four different models was consistent among the different trials such that SDP_H_Q resulted in the greatest benefit, which was more than two-fold greater than the worst performing model, SDP_N. Interestingly, the suggested models showed different behavior in the different storage and turbine capacity because the optimal release can be affected by relationship between power capacity, storage, and flows.

Figure 5-3 represents box plot for daily benefits with 50cms turbine capacity and large storage (10MCM). It can be assumed that the daily benefit variation can be interpreted as stability of model (Cote et al. 2011). SDP_N looks more varied performance than other models (i.e., SDP_H_S, SDP_H_Q, and SSDP_N).

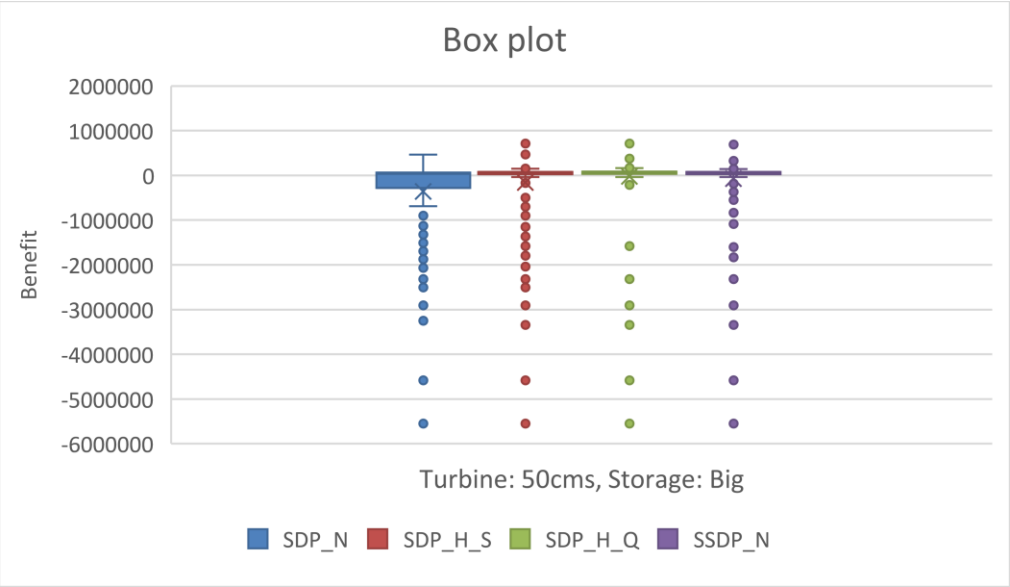


Figure 5-3 Box plot of daily benefit for 2016 inflows

Table 5-4 shows result of two-sided paired test, and difference between each model statically significant. This assumes the differences in performance from one day to the next are independent.

	SDP_H_S	SDP_H_Q	SSDP_N
SDP_N	5.36E-11	3.49E-22	1.87E-17
SDP_H_S		4.27E-09	1.72E-04
SDP_H_Q			1.37E-05

Table 5-4 P-values of a two-sided paired t-test of the difference between the simulated benefits

In this section, different results are observed in the modified benefit function with different turbine capacity and storage: 1) SSDP_N works better than SDP_N, 2) SDP_H works better than SDP_N, 3) SDP_H_Q shows the highest performance among the suggested models, and 4) the performance between each model is more pronounced in big storages compared to small storages. In order to examine differences between models, the original benefit function with a single term (i.e., power production) was modified by adding a penalty term for deviations from a storage target. As a result, the performance of each model started to differ because system operation now needs decision at each time step to efficiently generate power and maintain a certain water level to avoid penalty. Furthermore, other hydropower system objectives can also be addressed by using a modified benefit function in a mathematical way.

The next research question was to evaluate the value of possible forecasts. The hypothesis was that using better forecasts would lead to better policy performance. To identify the effectiveness of forecast quality, two different forecast variables were used: soil moisture generated by SSARR (a hydrologic model) and lag-1 current inflows. In fact, more time and effort were required to obtain forecast series from SSARR. The SDP with better forecast quality (i.e., SDP_H_Q) using current inflows resulted in the highest performance, better than SDP with poor forecast quality (SDP_H_S). Using current inflows as hydrologic state variable turned out to be most effective method in a daily time step optimization.

5.2 Model Resolution

5.2.1 The Number of Storage Levels

The common challenge in DP optimization is how to reasonably gain optimization accuracy without generating an unreasonable computational burden because the accuracy of the computation is highly influenced by the resolution of the partition of state variables (Klemes 1977; Tejada 1990; Piccardi and Soncini-Sessa 1991). Thus, in this case study, the number of 5 and 20 storage discretization intervals will be compared to examine the consequences of storage resolution on optimization performance and computation time. The result showed that same benefits were found between 5s and 20s storage partitions under different computation time: 5 storage (1min), 20 storage (3min) (Figure 5-4).

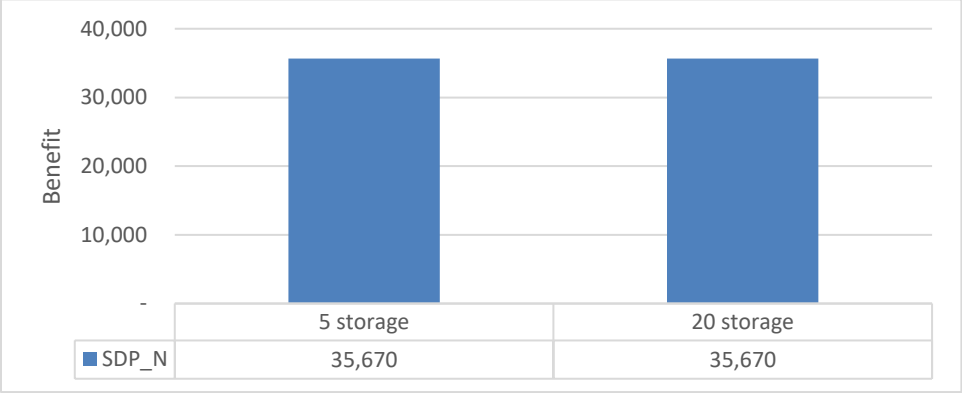


Figure 5-4 Benefit comparison between 5s and 20s storage (SDP_N) for 2016 inflows

At the beginning, the higher performance was expected with 20 storage level than 5 storage level. However, the same benefits were obtained from two discretization levels for storage. Therefore, appropriate storage resolution can be advantageous to develop efficient model in terms of computation time and model complexity.

5.2.2 The Number of Scenarios

For SSDP optimization, 51 years of historical inflows series were used as scenario sets in chapter 4. These scenario set could be reduced, but it could have impact to model performance due to losing information in each scenario. The assumption behind this approach is that SSDP performance could be affected by the number of scenarios employed because SSDP directly makes use of scenarios in the optimization and these scenarios represent the system status as a state variable in SSDP. Faber and Stedinger (2001) performed a case study to explore the sensitivity of model performance by adopting different numbers of scenarios in SSDP. They concluded that adopting a larger number of historical scenarios does not always guarantee improved SSDP performance. In the same context, although a smaller number of scenarios is used, the same resolution of optimization performance can be retained when scenarios with similar volume were combined. It can be anticipated that this approach will bring about alleviating computational efforts while model resolution is maintained by avoiding redundancy in similar scenarios. In fact, the time step used in this case study is daily. In this supplemental analysis the original 51 historical scenarios were reduced to 20 by random selection of the scenario, such as every other year.

Figure 5-5 shows performance comparison of SSDP_N between 20s and 51s scenarios: there was no difference in the model performance.

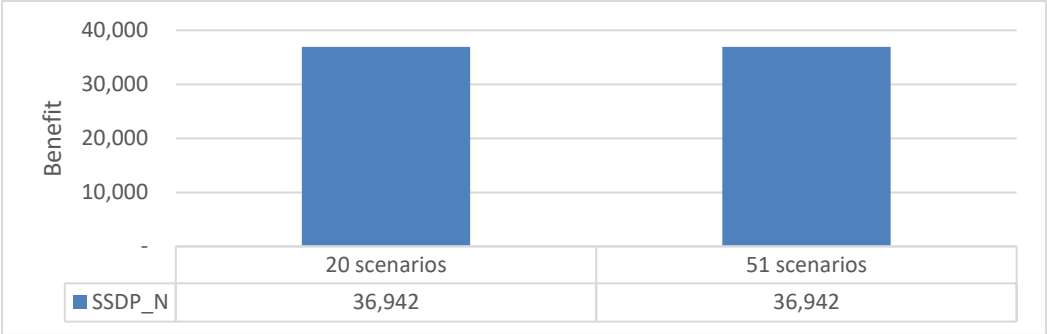


Figure 5-5 Benefit comparison between 20s and 51s scenarios (SSDP_N) for 2016 inflows

Additionally, the model execution time for the SSDP model with 51 scenarios took about three times longer than that of the SSDP with 20 scenarios. This increased computational time is due to the fact that the SSDP model with 51 scenarios needs to solve the optimization step 51/20 or 2.5 more times. This result agrees with a previous study (e.g., Faber and Stedinger, 2001) that a greater number of scenarios does not always guarantee better optimization performance. Thus, it makes sense to compromise between the conflicting components of computational time and model accuracy.

5.3 Summary

In this chapter, actual Bosungaang HPP system was modified with different system objective under different optimization configuration. The performance of each model was evaluated: SDP_H_Q is the most reasonably working with its daily current inflows information; SDP_N showed poor performance because of absence of hydrologic information. SSDP_N worked better than SDP_N in the absence of persistence. However, SSDP_N without modeling persistence did not work better than SDP_H_Q which included persistence. This chapter could provide beneficial information about existing hydropower system in case of future system expand or modification.

CHAPTER 6 SUMMARY, CONCLUSION, FUTURE WORK AND RECOMMENDATION

This thesis has addressed issues related to operation of hydropower systems when consideration is given to environmental impacts of release rates. Chapter 2 summarized the current knowledge on environmental flows and optimization methods in the context of hydropower systems. Chapter 3 outlined the background concerning the Bosunggang hydropower project in Korea as a case study. The potential for generating soil moisture data for the Bosunggang watershed using the SSAR model was evaluated. Chapter 4 developed two sets of hydropower optimization methods SDP and SSDP. They are non-structural options to address the impact of the legal minimum environmental flow requirement on power generation, and in all cases, might improve operations. In chapter 5, the models were further evaluated under different optimization constraints, including changing total project storage volume, number of turbines, and different penalties on storage target violations. In this final chapter, the analyses are summarized with two different perspectives: providing environmental flows and hydropower optimization method performance. Conclusions summarize the major findings of research. The final sections discuss future work and recommendations.

6.1 Summary

6.1.1 Environmental Flows Review

For a long time, hydropower has been recognized as a very promising renewable electric energy source because of its cost-effectiveness and potentially eco-friendly operation. Emerging climate concerns related to CO_2 emissions have further enhanced hydro's attractiveness. However, potential impacts to downstream ecosystems have been identified which mainly derive from natural flow regime alteration.

In hydropower systems, flow alteration results from two main processes: capturing stream flow and impounding these waters in the reservoir for future electricity generation, and regulating their release downstream under times of peak electrical demand and at controlled intervals. A general alternative to reduce this impact is to develop and implement the concept of minimum environmental flows as a conservative strategy that maintains some water downstream of the reservoir at all times. The most commonly used method to prescribe environmental flows is a habitat method, such as IFIM (Instream Flow Incremental Methodologies), because of its flexibility and ability to be applied to trade-off situations. This method can also be effectively used in determining the appropriate flow rules for sustainable river management.

Although viable approaches exist to integrate the value of hydropower with ecological sustainability, there are still several limitations to accurately quantify ecological value and achieve a balance between the two, which can be called a socio-economic trade-off. Jager and Smith (2008) suggested two common restrictions to solve such a problem: the evaluation of ecological benefits and quantification of ecological consequences from hydropower release.

Recognizing the importance of flow regimes could be a beginning step for sustainable hydropower operation and management. Furthermore, even if considerable dynamics exist in the underlying ecological mechanisms, more advanced strategies with generally acceptable tools will be expected at the initial step of planning hydropower plant to mitigate potential consequences in the future operation.

Challenges arose from maintaining power production in Bosunggang hydropower plant, Korea, and alternatives to hydropower system were investigated in this thesis. The pre-determined legal minimum environmental flow, 0.47 (m^3/s), was directly incorporated as a one of the constraints to develop two optimization models: SDP and SSDP.

6.1.2 Applications of Hydropower Optimization, SDP, and SSDP.

The primary objective of this research was to suggest viable alternatives to minimize the potential loss of hydropower generation while meeting the requirements of minimum environmental flows. This research evaluated two innovative reservoir optimization models: SDP and SSDP.

To account for hydrologic condition as a system state, two different forecast series were used with SDP. First, a soil moisture series was generated by a hydrologic lumped model, SSARR. The second forecast series used was the current period's inflows, lag-1. For the case study, the Bosunggang hydropower plant in Korea was selected and analyzed under diverse system configurations including scaling turbine capacities, different state resolutions, modification of the benefit function under varied penalty, and different numbers of scenarios in SSDP. Finally, the established optimal policy was then validated to see if it worked properly in the actual system with simulations. The case study results support five main discoveries.

First, including a hydrologic state variable in SDP models produced better performance. Second, the more informative and high-quality forecast variables resulted in better optimization performance. Third, using different storage partitions and different number of scenarios did not yield significant improvements in optimization performance, even if denser model resolutions were used with extra effort and computation time to build a model. Thus, finding an appropriate threshold of discretization levels is necessary in both SDP and SSDP. Fourth, threshold of effectiveness of hydropower optimization under increased minimum environmental flows constraint was investigated. The optimization could cover up to 2 (m^3/s) of minimum environmental flows to keep power production as the same level as was exhibited in historical records.

Lastly, most importantly, regardless of which type of SDP and SSDP optimization model was used, the annual power generation increased in comparison to the existing system historical record, while satisfying legal minimum environmental flows. Moreover, under optimal operation, downstream spillage is reduced as compared with the existing operation record. This finding means that keeping water in the reservoir without unnecessary spills can eventually increase the flexibility of reservoir operation because the impounded water can be used for future energy generation. However, this extra spillage could alternatively be used to address a different component of environmental flows, that is, for restoring seasonal high flows which inundate adjacent wetlands and support fisheries, especially during the monsoonal months. Environmental ecosystem restoration can benefit from many changes in operation from minimum flows as a function of season, increases or decreases in flow variation, temperature control, and occasional floodplain inundation. Overall this research shows that SDP and SSDP can effectively and economically compensate for new ecological constraint in hydropower system as well as increase power production.

To summarize, simply adopting sophisticated models without careful consideration of system characteristics, does not guarantee optimization improvements nor shorter times to reach the optimal solution. Careful consideration in building reasonable SDP or SSDP model should be given to 1) selecting suitable forecast variables to account for the basin hydrology of the surrounding reservoir with adequate forecast lead time, 2) finding the appropriate system state variable aims at balancing computational efficiency and model resolution in SDP and SSDP.

6.2 Conclusion

The four major conclusions of this research are:

(1) Although the ecological requirement in hydropower systems can be represented by a quantifiable proxy such as a minimum environmental flow, further diagnostic and integrated approaches are required to more accurately represent the dynamics in eco-system habitats;

(2) Application of both SDP and SSDP optimization methods for the Bosunggang hydro power plant in Korea increased the amount of power generation in comparison to the existing system operation while satisfying the legal minimum environmental flows in downstream;

(3) SDP and SSDP reservoir optimizations reduced unnecessary downstream spill so that it could potentially allow greater power generation and flexibility in future operations;

(4) Optimization models employing dense state discretization or including a hydrologic state variable did not always guarantee better performance in the absence of thorough understating of the basin's hydrology. Therefore, system characteristics should be carefully considered to build more efficient and practical optimization models.

6.3 Future Works

6.3.1 Incorporation of Advanced Forecast Technique

The major assumption in this research was that the use of 51 years of historical inflow and soil moisture forecast factors to develop optimal release policies was adequate to reflect future system states. However, such assumption did not take unpredictable future events into account, such as prevailing climate change, the market fluctuation, and hydrological uncertainties (e.g., severe drought and flood). Among these possible circumstances, the reservoir operation of hydropower system is the most sensitive to hydrological uncertainties. Under extreme hydrological conditions, future system states could be significantly different from the pre-established state policy derived from reservoir optimization at the present time.

As an alternative, future hydrological conditions can be better predicted by more advanced meteorological forecast techniques. For example, Extended Streamflow Forecasts (ESP) has been frequently combined with SSDP, and it has turned out to be well-performed in reservoir optimization (Faber and Stedinger 2001; Kim et al. 2007; Eum and Kim 2010; Kim et al. 2011; Eum et al. 2011). This extended version of SSDP combining with ESP is capable of improving the reliability of optimization by handling a wide range of unexpected future system states in reservoir operation.

Therefore, for a future study, the synchronization of optimization and metrological forecast will be promising research work to obtain more reliable forecast for hydropower operation so that more stable and instantaneous reservoir operation decisions can be ultimately made.

6.3.2 Multiple Reservoir Hydropower System with Multiple Objectives

In this research, SDP and SSDP optimization algorithms were applied into a single reservoir. However, two subsequent dams (i.e., Juam dam and Sumjingang dam) are located right underneath of the Bosunggang HPP system. To carry out integrated water resources analysis and management with close interaction between each hydropower system, multiple reservoir optimization can become a valuable pursuit. In addition, to adapting to the emerging new roles of reservoir in the future (e.g., water supply and flood control), the single purpose of Bosuggang reservoir in this study can be expanded into multi-objective problems. These works could build more practicable hydropower optimization models with more integrated perspectives in cascade hydropower system.

6.3.3 Integrated Minimum Environmental Flow

Instead of solely basing on the traditional approach in prescribing minimum environmental flow such as one dimensional physical habitat model, future work could adopt a multi-dimensional environmental river simulation model (e.g., river 2d, flow 3d) to accurately assess ecological features. This could lead to ultimately accomplishing sustainable and eco-friendly hydropower operations by coupling with efficient reservoir optimization techniques.

In this study, the impact of pre-determined minimum environmental flow, 0.47 (m^3/sec), was used in the optimization as a constraint. However, this value was derived solely based on a simple analysis that considered the minimum hydraulic condition for fishery habitat. In contrast, a more integrated ecological model, Physical Habitat Simulation System, PHABSIM (Milhous et al. 1993), proposed a higher value of 1(m^3/sec) as a value for sustaining optimal fishery habitat. Therefore, more detailed site investigation and further research defining ecological schemes and habitat in target site

are necessary such as fish migration, water quality, and spawning (Ferreira and Teegavarapu 2012).

6.4 Recommendations

6.4.1 Sustainable Hydropower Energy

Continuous effort is needed to overcome often conflicting issues to effectively manage limited water resources. This will eventually bring balanced gains between environmental preservation and restoration versus economic profits in the future, which will be the foundation of establishing sustainable hydropower operation.

Although hydropower is definitely an eco-friendly energy source with competitive prices compared to other renewable energy sources, discrepancies exist among interested parties. For instance, the implication of minimum environmental flows for a hydropower system as a role of safe-guard can be interpreted in different ways; while environmental advocates emphasize ecological protection, hydropower plant's owners focus more on meeting human living demands. Under these competing circumstances, ensuring sustainable hydropower plant operations can serve as means to harmonize between surrounding creatures and human demands. Although, addressing minimum environmental flows can be regarded as an obligation to hydropower agency, it can be successfully dealt with by using a non-structural engineering approach such as SDP and SSDP optimizations without supplementary costs as proved from this research.

6.4.2 Application of Optimization Model into Real System

Continuous intercommunication between modelers and operators at the initial phase of hydropower system optimization is a necessary effort to build a more practical and usable model. Such collaboration can lessen the ordinary gap between models and actual operations. Under the circumstances of diverse reservoir demands and the unpredictable impacts on hydropower system brought by current climate changes, more advanced and flexible operation skills are needed to overcome these emerging challenges.

Hydropower optimization method is definitely a feasible solution due to its capability in aiding operators to take an action competently under a variety range of system variation. However, an inherent limitation has existed in real-world applications because of the operators' tendency to rely on operation manuals with long-term policy, simple simulation tools, and their own prior experiences (Labadie 2004). Furthermore, most studies on reservoir optimization fairly focus on finding a desirable mathematical algorithm to solve the problem efficiently, whereas in real world implementation, dam operators have the propensity of exploring practical operational strategies (Eum et al. 2005; Ahmad et al. 2014). In the near future, it is anticipated that without continuous monitoring of previously developed optimization model, operators will continuously rely on the traditional approach as before.

Therefore, it is recommended that future work should focus on how to overcome these challenges, and how to practically apply the developed hydropower optimization models into existing system with a sensible approach.

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