DISSERTATION

A NEURAL – OPTIMAL CONTROL ALGORITHM FOR REAL-TIME OPERATION OF COMBINED SEWER SYSTEMS

Submitted by

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WE HEREBY RECOMMEND THAT THE DISSERTATION PREPARED UNDER OUR SUPERVISION BY SUSENO DARSONO ENTITLED A NEURAL – OPTIMAL CONTROL ALGORITHM FOR REAL-TIME OPERATION OF COMBINED SEWER SYSTEMS BE ACCEPTED AS FULFILLING IN PART REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY.

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ABSTRACT OF DISSERTATION
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Most urban populations are growing rapidly worldwide. at unpredictable rates, which increases the quantity and reduces the quality of the storm water discharge. During the flood period, urban drainage areas that have combined sewer networks may directly release part of the drainage water into the receiving water. Therefore, two objectives of real-time control for urban drainage system are to reduce the amount and the frequency of damage, and to reduce the environmental impact caused by pollutant discharges. In the last decade, there have been many attempts to improve and to maintain the urban living environment by improving the efficiency of the combined sewer system. Researchers are still searching for an efficient optimization or a control technique toward simplification of analysis and reducing the requirement of computer time and memory.

The rainfall-runoff module, the flow routing module, the optimization module, and the neural control module are four modules that are required for the real-time control model of the dissertation. The main purpose of the dissertation is to explore and to demonstrate an effective dynamic neural network model for the real-time control module. The rainfall-runoff module uses kinematics wave routing techniques to simulate the rainfall hyetograph become an inflow hydrograph. The Preissman Four-Point implicit scheme is the technique to solve the St. Venant equation in the hydraulic or flow routing module. The neural control module is Jordan's neural network architecture. The training process for the neural control module uses optimal policies that were produced by the

optimization module as the reference of the desired output. The optimization module uses the Fletcher-Reeves conjugate gradient method to solve the direct optimization algorithm of a discrete form for the Potryagin's Maximum Principle (Optimum Control Theory).

A typical three-layer of an artificial neural network with Jordan architecture gives a good result of dynamic urban drainage real-time control. The training or learning process is a step to estimate parameters or weight of the neural networks. The back propagation learning technique is a simple and a common supervised learning technique for determining the model weights. The testing process is a validation of the weights that were produced in the training process. The neural control module is considerably faster to evaluate and to determine optimal gate openings. Therefore, an artificial neural network technique is an effective and a viable tool for a real-time control module. Many possibilities for further research in the area of learning technique and application of the model are still open.

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I. INTRODUCTION

1.1. Impact of population growth on urban storm water management

As urban populations worldwide continue to grow geometrically, increasing pressures are placed on arable land, water, energy, and biological resources (Pimentel et al., 1996;Simonovic, 2000; Nirupama, and Simonovic, 2004). With approximately half of the world's population living in urban areas (Tucci, 2001; US-EPA, 1997), these increasing human concentrations and services require rapid development of urban facilities that relate to the urban living environment. Urban storm drainage, water supply, solid waste and sewage disposal are components of urban facilities that need to be developed and adequately maintained.

In particular, investigations on development of effective storm water management practices to overcome the negative impacts of urbanization are required (Li et al., 1998; Loucks et al., 1997). The following conditions directly influence the quality and quantity of urban storm water discharge including conditions of the hydro-ecological system, ecological diversity, and public health (Loucks et al., 1997):

1. Increasing population density.
2. Land use changes resulting in increased impervious area and drainage channel density.
3. Increasing urban residues and pollution sources.

The quality of urban storm water runoff also changes because of reduced infiltration in the urban watershed and accumulation of urban residues such as oil, gas, etc. (Smith and Bedient, 1980, Li et al, 1998). Since urban storm water drainage impacts the environmental condition of downstream areas, an urban drainage management system should be considered as a part of a regional or river basin management system (Tucci, 2001; Schultz, 2000). Regional storm water management is an important aspect for maintaining a quality urban living environment (Lee and Dinar, 1995, Azevedo et al., 2000).

Some aspects requiring consideration during the planning of urban drainage management systems are: proper institutions, reliable regulations, and the use of management models (Haan, et al., 1978; Chaturvedi, 1978; Lee and Dinar, 1995). Many attempts have been made to improve or to maintain the urban environment through real-time urban drainage control systems as a part of an urban storm water management system. Improvements in urban drainage control systems may reduce excessive flooding, stream-bank erosion, and receiving water pollution, as well as increase property values and wildlife habitat (US-EPA, 1995; Behera et al., 1999).

1.1.1 Need for optimization in urban storm water management

Design, construction, operation, and maintenance of urban drainage systems require extensive financial resources. Therefore, one objective of upgrading urban drainage and wastewater urban storm drainage systems is to provide a maximum level of protection at minimum cost. Researchers have discovered that optimization techniques can help achieve an optimal plan and design of urban drainage systems and reduce the total of construction costs (Merritt and Bogan, 1973; Dajani and Hasit, 1974; Jacobs and Medina, 1994; Reyna et al., 1994). These techniques can also be used to establish optimal operational schemes for existing urban storm drainage systems.

Many public and government agencies (such as the Environmental Protection Agency, USA and the National Water Research Institute, Canada) are seeking attractive alternatives through optimization techniques and computer control to improve efficiency of urban water management systems. To achieve an optimal urban drainage control system, efforts are ongoing to find new techniques in urban storm water modeling that can combine efficiency and the ability to find global optimal solutions (Simonovic, 2000).

1.1.2 Real-time control of combined sewer systems.

A combined sewer system (CSS) is a type of urban drainage network built for collecting and transporting both urban wastewater and storm-water. Figure 1 shows common elements of a typical combined-sewer system, what are generally found in older cities. Minimizing direct spills from the combined sewer systems is the main goal for an optimal CSS operation. Real-time control (RTC) operation is a tool to attain optimal operation of a CSS. Real-time control of a combined sewer system requires a fully integrated control system to optimize all gates and pumps operation within the system.

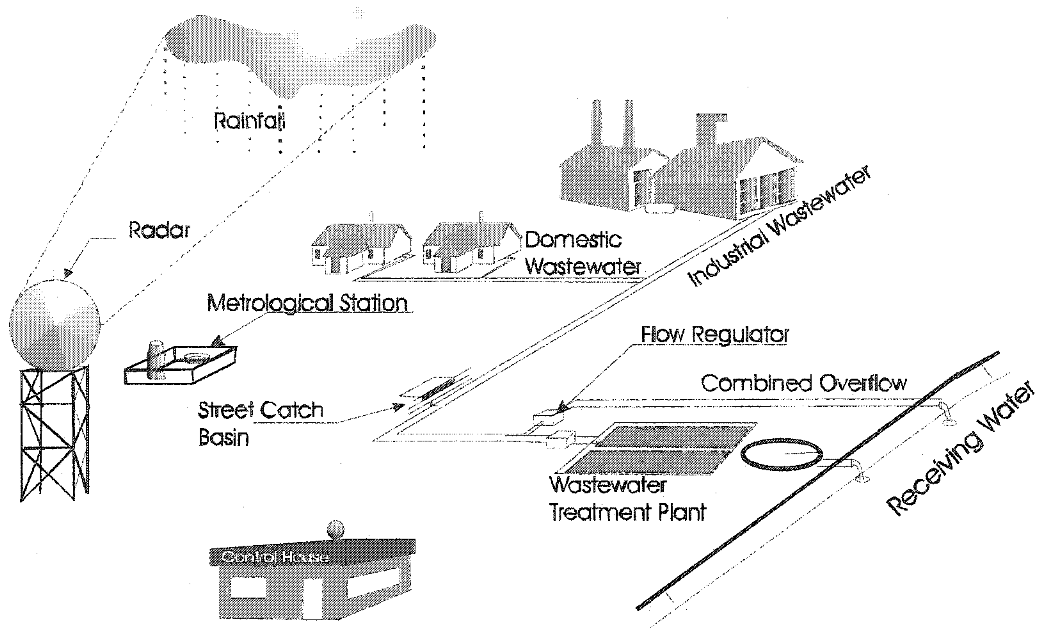

Figure I-1 Typical elements of real-time control of combined sewer system's

During wet weather conditions, storm water flows to the CSS are distributed in time and space, the available capacities are not homogeneously distributed, and the system outputs are also non-static in time and space (Nelen, 1994). The following items are the main objectives of the CSS real-time control operation (Nelen, 1994; Labadie, 1993; Dellatre, 1990):

1. Maximizing in-line and/or off-line storage capacity for reducing the amount and the frequency of urban flooding.
2. Minimizing direct overflows to the receiving waters to reduce environmental impacts caused by pollutant discharges.

Effective real-time control requires a set of computer models to provide actual optimal decisions and information for the decision-makers and operators. Most of the researchers found that the real-time model with an optimization module (such as dynamic programming, optimal control theory, linear quadratic programming, non-linear programming, and integer programming) could increase efficiency of the systems (Ormsbee and Lansey, 1994; Labadie, 1993). Real-time control of urban storm drainage or combined sewer systems can be categorized as large scale and complex systems. The following items are measurement and control devices that are required for achieving optimal operation of the systems (Chantril, 1990; Speer et al., 1992; Labadie, 1993; Ormsbee and Lansey, 1994):

1. Remote measurement devices for measuring rainfall, flow rates, water levels, pump station status, gate positions, regulator stations status and alarm information.
2. A reasonably accurate rainfall-runoff model for estimating inflow data from measured rainfall data and/or from a short term forecasted rainfall.
3. A sewer transport model or a hydraulic model used to simulate flows through the conveyance system, including control devices and pumping stations.
4. Dependable telecommunication and database management systems are required for transferring and processing information in support of the models, such as accurate rainfall and flow data.
5. An effective optimal control model by which control policies can be updated as a storm progresses, based on successive storm predictions.

6. Remote pneumatic, hydraulic and electrical-mechanical devices are required for controlling gates, weirs, orifices, and pump stations.

Wastewater and storm sewers can be classified as two different sub-systems of urban water management. At times, they function as a combined urban sewer scheme, with many cities around world still using combined sewer systems to drain dry weather flows and wet weather flows through treatment plants. During a high flow event, however, untreated spills to the receiving water may occur in these systems. Separated urban drainage systems also require treatment facilities, since storm water alone may be contaminated with pollution from non-point sources. A real-time control operation is a viable technique for improving the efficiency and cost-effectiveness of either existing combined sewer systems or urban storm water drainage systems.

1.2. Objectives

Real time operation of combined sewer systems is a reliable and efficient technique in reducing direct overflow of storm water to a water body. However, the complexity of combined sewer system hydraulic modeling and the need for dynamic, fully integrated control over an urban area can require computational execution times that exceed the short-term time intervals for effective real-time control. Many attempts to simplify simulation or optimization models have been conducted (Mailhot et al., 1999; Pleau et al., 1996; Gelormini and Ricker, 1994; Marinaki and Papageorgiou, 1997; Labadie, 1993). Rainfall data or inflow forecast data are the primary input to the hydraulic routing and optimization models for producing real-time optimal control solutions. Therefore, computer execution time of the real time model should be less than the computational time-step required for effective control during a rainfall event (Stirrup et al., 1997). As an alternative approach, it is hypothesized that the simulation and optimization models can be run offline for wide range historical rainfall inputs. These inputs, along with the resulting optimal controls (e.g., gate and pump stations operations) can then serve as a training data set for a dynamic or recurrent artificial neural network (ANN). Successful training of the ANN would provide rapid implementation for real-time controls, with full consideration of complex hydraulic condition in the combined sewer network. Dynamic or recurrent artificial neural networks have the advantages of high analysis speed, good generalization ability and high fault tolerance. This model can also solve large and complex problems which are traditionally difficult for a conventional model to solve. The objectives of the dissertation can be stated as the following items.

1. Evaluate the capability and the purpose of four major modules.
2. Elaborate and review all general formulations for optcon and neural dynamic modules.
3. Explore the ability of Jordan architecture network as a dynamic neural control model.
4. Conclude the primary contribution of the dissertation to the field of water resources and urban drainage operation.

1.3. Purpose

The primary purpose of this study is to explore and demonstrate the effectiveness of application of dynamic artificial neural networks as the real-time control module for urban drainage and combined sewer systems. Comparison of the results of the optimal control module and neural control module is utilized to evaluate performance of the artificial neural networks. The combined sewer network of the West Point System of the Metro Seattle Area is selected as a case study demonstrating the viability of the neural-optimal control methodology.

1.4. Scope of work

According to the objectives and the purpose of this study, the following defines the scope and major stages of this research:

5. Evaluate the operational problems for urban drainage systems and formulate the possible strategies and problem solutions.
6. Conduct a review and summarize related literature for selecting appropriate and dependable techniques for solving the real-time operation problems in urban storm water management.
7. Modify the control or operation module of the available real-time control models for combined sewer systems.
8. Apply and evaluate the dynamic artificial neural networks as the proposed real-time control model.
9. Evaluate and compare the ability and dependability of both the present and proposed model.

1.5. Methodology

An optimal real-time control study for urban storm drainage and combined sewer management requires reliable computer models for predicting inflow, hydraulic-routing and controlling storm water flow. The following list is a brief summary of the contents of this dissertation.

1. A literature review related to real-time storm drainage control is presented in Chapter 2. The review focuses on solution techniques and general algorithms for inflow forecasting, hydraulic routing and operational or control techniques.
2. Chapter 3 describes the fundamental governing equations and basic algorithms of the modules.
3. Chapter 4 presents a case study for demonstrating the performance of the model. The case study focuses on optimal real-time operation for an urban drainage network in the West Point System of Metro Seattle. This chapter presents the results of training, and testing of the neural optimal control module.
4. Chapter 5 provides conclusions of the dissertation and recommendations for future research.

II. LITERATURE REVIEW

Most urban drainage systems in large cities have some combination of urban storm drainage and municipal sewerage (wastewater) systems. During wet weather conditions, the storm water flow may exceed the treatment plant capacity, resulting in untreated spills directly to the receiving water. The real-time control (RTC) is a technique to reduce quantities and frequencies of basement floods, and direct spills by regulating flows (Chantril, 1990; Nelen 1994, Marinaki et all, 1999). Maximizing detained storm water in the system is a possible method to minimize direct untreated spills to the receiving water. Computer systems are required to produce optimal flow regulations of operation strategies of the systems for decision makers and operators (Stison, et al., 2000). The potential surcharge flows into basements or streets, and the sedimentation in the storage facilities and increasing operation and maintenance cost are three drawbacks and limitations of CSS real-time operation (U.S. EPA, 1999). The control strategy favors surcharges of some sewer pipes, as long as the pressure resistance of pipes is not exceeded and water heights do not reach levels resulting in potential flooding hazards (Duchesne, et al., 2004). Physical works, legal policies and political considerations are three important aspects in the real-time operations for urban drainage systems (Delattre, 1990).

A combined sewer operation using a real-time control technique is a good approach to manage and control the use of the existing system. The real-time control is required to be implemented before additional storage facilities are necessary (Delattre,1990). Several investigations dealing with the implementation of RTC in Combined Sewer Systems have been conducted. RTC was demonstrated as practical, feasible and efficient technology to regulate Combined Sewer Systems. Minneapolis-Saint Paul, MI; Metro Seattle, WA; Rochester, NY; Cleveland, OH; Detroit, MI; Chicago, IL; Milwaukee, WI; San Francisco, CA; are eight cities in the United Stated that implement the RTC technology. The Montreal Urban Community – Canada also utilized RTC to operate the combined sewer system. In Europe, the RTC system has also been applied to the following cities: Bordeaux, Hauts-de-Seine, Marseille, Metz, Nancy, Seine-Saint-Denis, Val-de-Marne and Paris in France; Bremen, Hamburg, Munich and Stuttgart in Germany; Berne, Fribourg, Geneva and Lausanne in Switzerland; Göteborg in Sweden; and Copenhagen, Aalborg in Denmark (RTCUSDS, 2004; Loucks, et al., 2004; Stirup, et al., 1997; Vitasovic, et al. 1990; Anderson, et al. 1997).

Both optimization and simulation modules are important and are required modules in a real-time combined sewer overflows (CSOs) control model. There are two main purposes for the real-time CSOs control model. The first purpose of a simulation module is to determine flood hydrographs using hydrology analysis, and to evaluate the optimal gates opening and storage levels using hydraulics routing analysis. The second purpose of the model is to determine the routing parameters and the constraints for the next cycle analysis using the optimization module (Albuquerque, 1993; Albuquerque an Labadie, 1997).

Thus, the first component in the simulation module of the real-time CSOs control model is a rainfall-runoff model. A hydraulic routing model that is used to route flow throughout the urban drainage network up to the treatment plant and to the receiving water is the second module (Huber, 1988; Lyngfelt, 1991; Mihocko, et al., 2002; Loucks, et al., 2004). The first simulation module of the real-time combined sewer system control model (rainfall-runoff module) can analyze overland flow and flood routings for gutter, or minor drainage channels. The following items are the required steps for simulating a flood hydrograph from each designed entry point of the combine sewer network (Viessman et al., 1977: Grene and Cruise, 1995; Cassar and Verwon, 1999; USACE, 2000):

1. Measured rainfall hyetographs as a major input of the hydrograph analysis is the initial step of the analysis (Maršálek, 1978; Book, 1980 and Arnell, 1982; Bedient et al.2000).

2. Evaluate the losses and excess rainfall rate that includes infiltration loss and detention storage is the second step of a flood hydrograph analysis. Several available methods or techniques for evaluating infiltration loss are the Horton's, Holtan's, and Green Ampt equations.

3. Determine hydrograph for each watershed by means of an overland flow analysis is the next step of the analysis.

4. Route the flood hydrograph through gutters or minor drainage channels to determine inflow hydrographs for each designed entry point of major drainage networks is the last step of the analysis.

The rainfall-runoff module of the real-time control model will determine or estimate the synthetic flood hydrographs. The short time duration of rainfall-runoff models generally does not consider or simulate soil-moisture, evapotranspiration, interflow, or base flow process (Viessman et al., 1977; Becciu and Paoletti, 2000; USACE, 2000). Short durations with high-intensity rainfall events are typical data of the rainfall-runoff module of the urban drainage simulation models (Schultz, 2000). Historical flood hydrographs are utilized to calibrate model parameters (Grimes et. al, 1999).

2.1. Rainfall data

Measured rainfall data are input of rainfall-runoff module of the real-time control model. Automatic rain gauges or radars will measure accurate real-time rainfall intensity as well as the space-time variability of the data (Ogden et al, 2000, Torres et all, 1999, Finnerty et all, 1997). A combination between radar and rain gauges will improve the result of hydrographs forecasting (Torres et all, 1999, Johnson et all, 1999, Seo et all, 1999). A method of merging rain gauges data and satellite data seems a promising technique for estimating short time distribution of rainfall data. In developed countries, radar has played an increasingly important role in rainfall data measurement (Grimes et.al, 1999).

2.2. Rainfall-runoff simulation module

Several studies have reported the result of qualitative and quantitative analyses of rainfall-runoff models such as the KINEROS (Woolhiser, et al., 1990), EPA-SWMM, ILLUDAS (Terstriep and Stall ,1974), and MOUSE (Danish Hydraulics Institute, 1996). Zarriello, (1998) and Trommer, et. al., (1996) conducted a qualitative comparison of the Rational method, EPA-SWMM, HEC-1, TR-20, HSPF, PSRM and DR3M model. Zarriello, (1998), Trommer, et. al., (1996), Heeps and Mein (1974), Maršálek et al. (1975), and Huber (1975) conducted other related comparative studies. These studies generally conclude that there is no single model with universal capabilities. Verification and validation are two important steps in determining the model parameters based on objectives and applications of the model (ASCE Task Commitee, 1993; Trommer et al., 1996). Book (1980) selected the RUNOFF block of the San Francisco Storm Water Model for a hydrograph runoff prediction, which is similar to the RUNOFF block of the EPA SWMM model. Book (1980) modified the infiltration analysis by adding a Green Ampt infiltration model as an alternative equation to Horton's equation (Labadie, 1993; Book, 1980).

The most important problem that is usually faced in the application of the urban runoff model is the decomposition of the catchments followed by the transformation of catchment characteristics into "input data." A coarse description of the catchments will often result in a poor model performance (Yen and Akan, 1999). On the contrary, detailed descriptions of the catchments are ineffective and very costly (Lyngfelt, 1991; Book, 1980). Simplifications of the shape of drainage area or catchment areas are important steps for modeling purposes (Basha, 2000).

Shallow water analysis is the basic approach for free surface flow on overland flow, gutters and in sewers (Yevjevich, 1975). Some hydraulic routing models apply the kinematics wave equation for predicting the runoff (Basha, 2000). Qualitatively, the kinematic wave approximation is an appropriate technique to route flow over steep slopes where the Froude number is less than two. For practical purposes, there are two other modifications of the kinematic wave equation. The first modification is a nonlinear reservoir model, which uses a spatial lumped continuity equation and a storage discharge equation (Basha, 2000). A time-area model is another modification of the kinematic wave equations. The major assumption in this model is constant flow velocity in time, but not in space (Lyngfelt, 1991).

The following items are the general steps involved in the digital simulation of urban runoff:

1. Determine the rainfall pattern and intensity, and then determine the rainfall distribution over space. The Theissen polygon method is often used to determine the spatial distribution of rainfall from the point rainfall gauge data.

2. Analyze rainfall abstractions and calculate effective rainfall. Most urban runoff ignores rainfall abstractions from interception, evaporation, and transpiration, but includes depression storage and infiltration which are an abstraction on the catchment area (Kidd, 1978). Some methods are available for estimating depression storage such as the European method and the Viessman's method, but the EPA SWMM model treats depression storage as a calibration parameter (Huber and Dickinson, 1988). Most of the urban runoff models utilize the Green-Ampt equation and Horton's equation for estimating infiltration losses.

3. Calculate the overland flow to gutters and minor sewers using the overland flow routing techniques. Under certain conditions the kinematic wave gives reasonably accurate result for the overland flow model (Akan, 1993).

4. Route gutter flows to sewer system inlets using the kinematic wave or the full dynamic wave technique.

2.3. Hydraulic routing module

An urban drainage system is generally a dendritic network of channels or pipes. Urban drainage flow is an unsteady, non-uniform, turbulent, and sub-critical open-channel flow. At the beginning of a storm period, open channel flow conditions prevail in the storm or combined sewers. As the storm event progresses, surcharged or pressurized flow conditions may occur. Surcharged flow conditions may occur when the storm event exceeds the design capacity of the systems. In addition, inadequate maintenance of sewers may cause surcharge flow conditions (Yen, 1986). A fictitious Priessman Slot is required to extend the capability of the one dimensional unsteady analysis for free flow conditions in a closed conduit to surcharged condition. Top width of the slot is introduced to modify the concept of computation. The top width is assumed to be 0.1% of maximum width of a conduit under surcharged condition. Therefore, no additional area and wetted perimeter are added from the slot (Ji, 1998).

Chen and Chai (1991) modified the Book's (1980) UNSTDY model, to handle drainage networks that have branching systems and looped systems with free surfaces, pressured flows and laterals inflows. Equipment that is used to regulate flow in the drainage networks are radial or sluice gates, overflow weirs, siphons, in-line, and off-line storage basins, in line and side orifices, and pumping stations.

The complete Saint-Venant equations are required to evaluate the fully dynamic unsteady flow condition in sewer systems. The method of characteristic developed by Stoker is the earliest numerical solution technique based on calculation characteristic curves representing the path of disturbance propagation (Stocker, 1953; Sinha et al., 1995). The numerical approximation method is required to solve these equations (Choi, 1991; Chen and Chai, 1991; Yen, 1986; Samani and Jibelifard, 2003). The numerical approximation methods require a large amount of computer storage and computing time. To reduce the size of the matrix equations, Sevuk and Yen (1973), Akan and Yen (1981) introduced an iterative successive overlapping segment technique in the flow routing of dendritic channel networks. However, large numbers of iterations are required when the downstream backwater effect is significant. The simultaneous solution technique with double sweep algorithm is another alternative to simplify the calculation for many types of channel network (Choi and Molinas, 1993; Nguyen and Kawano, 1995).

There are three steps for solving these equations using the finite difference method (Choi, 1991; Choi and Molinas, 1993; Nguyen and Kawano, 1995):

1. Determine a finite difference mesh to represent the prototype continuum and the type of finite difference approximations.
2. Determine a method to represent the result of the algebraic equations.
3. Select a method to solve the solution of linear or nonlinear algebraic equations.

2.4. Urban drainage operation module

Reactive (or myopic) control and adaptive (or anticipatory) controls are two basic approaches in the real-time control of a storm and combined sewer system (Duchesne, et al., 2004). In the reactive approach, control decisions are based on current rainfall data, flow data and storage data (Stison, et al., 2000). In contrast, control decisions in an adaptive approach rely on current conditions as well as future anticipated conditions and rainfall forecast. The adaptive approach, therefore, requires more sophisticated on-line computer capability, both software and hardware. With this approach, forecast accuracy directly impacts the effectiveness of real-time control decisions. Physically based models and statistical models are two basic approaches that are useful for forecasting rainfall data over short intervals. Physically based models require sophisticated computer technology and communication systems. On the other hand, statistical models are black box models that attempt to find correlative patterns of telemeter spatially distributed meteorological data for extrapolating forecast information (Labadie et al., 1981; Stison, et al., 2000).

Filipovic and Milosevic (1989) used dynamic programming for optimal control of water flow in open channels. Since dynamic programming incurs the well-known "curse of dimensionality", the proposed model is only applied for two successive periods. Papageorgiou (1983, 1985 and 1986) applied a discrete optimal control theory to the operation of a combined sewer system and a multi-reservoir network. The optimal control algorithm employs a penalty function for state-space constraints. Generally, both computational storage space and computing time increase linearly with the dimensions of the problem. Application of optimal control theory to large systems becomes more difficult when state-space constraints are explicitly included in the optimal control algorithm without use of penalty functions (Grygier, 1983). Labadie (1993) also developed a real-time operational model using discrete optimal control theory for optimal regulation of an in-line system storage in a combined sewer.

Grygier and Stedinger (1985) presented a comparative evaluation of several optimization techniques for operation of multi-reservoir hydropower systems. This study compared application of optimal control theory, successive linear programming, and dynamic programming assuming deterministic inflows. The application of optimal control theory was slightly faster as compared with other techniques for simple systems, but was more difficult to implement. Hiew (1987) conducted an evaluation comparing applications of five optimization algorithms to a hypothetical five reservoir hydropower system. The algorithms included incremental dynamic programming (IDP), successive linear programming (SLP), feasible direction method (FDM), optimal control theory (OCT), and objective-space dynamic programming (OSDP). Nonlinear optimal control theory (NOCT) was the most efficient, robust, and flexible optimization method for sewer network (Marinaki and Papageorgiou, 1997). In contrast with the method explored (Grygier and Stedinger, 1985), state-space constraints were implicitly considered through use of penalty functions. Criteria for the evaluation included accuracy of results, rate of convergence, smoothness of storage and release trajectories, computer time and memory requirements, robustness, and other pertinent considerations.

Quarda (1991) conducted an evaluation for large-scale hydropower systems using stochastic optimization. The evaluation compared stochastic-dynamic programming, implicit stochastic dynamic programming, and chance constrained optimal control theory. The result of the evaluation showed that the chance constrained optimal control had the most satisfactory performance.

2.5. Neural networks control module

The architectures of neural networks are imitations of the structure of the human biologic neural systems. Artificial neural network (ANN) models are a type of information-processing system that utilize parallel distributed processing capable of approximating arbitrary nonlinear functions and may have great potential in the field of real-time nonlinear control problems (Rao and Gupta, 1994). In the field of water resources, Rasul and Paudyal (1994) proved ANNs were useful for real-time control of hydraulic structures. Compared with conventional real-time control techniques, an ANN may avoid the complicated mathematical operations require for a real-time operational model of a system (Rasul and Paudyal, 1994). An ANN may be useful for operating or controlling an urban drainage system under real-time conditions, since neural networks have the following features for the control context (Hunt and Sbarbaro, 1991).

1. Ability to interpret arbitrary nonlinear relations.
2. Ability to adapt and learn the characteristics of complex system behavior.
3. Ability to transform information into internal representations by allowing data fusion using both quantitative and qualitative signals or inputs.
4. Parallel distributed processing architecture allowing rapid processing for large-scale dynamical systems.
5. The architecture of neural networks can provide a degree of robustness through fault tolerance and graceful degradation.

Hsu et al. (1995) explained the applicability of neural networks for simulating dynamic systems in science and engineering and Govindraju (2000) examined the role of ANNs in various branches of hydrology, and it was found that ANNs are robust tools for modeling many of the nonlinear hydrologic processes. The rainfall-runoff model (Tokar,, and Johnson, 1999), daily and hourly stream flow forecasting (Kang et al., 1993), forecasting the complex temporal and spatial distribution of rainfall generated by a rainfall simulation model (French et al., 1992), and application of networks in design of coastal sewage systems (Sanchez, et al., 1998) are examples of the use of neural networks in hydrology.

Many researchers have investigated the use of neural networks for solving non-linear dynamic control problems. Narendra and Parthasarathy (1991) explored the use of a neural network for identification and control of dynamical systems. Hunt and Sbarbaro (1991) examined neural networks for non-linear internal model control. Parisini and Zoppoli (1994) applied an ANN for a feedback and a feed-forward nonlinear control system. They concluded that the technique is effective for solving non-linear dynamic control problems. The conventional control techniques require complex mathematical models for describing the dynamic behavior of the plant or the system. Multi-layered and recurrent neural networks are two classes of neural networks which have received considerable attention in recent years. The multi-layered neural networks have proven extremely successful for pattern recognition problems. In addition, recurrent networks incorporate capabilities in associative memories for solution of optimization problems (Narendra and Parthasarathy, 1990). In many engineering, scientific, and economic applications, the need arises to utilize dynamical neural network models (Hassoun, 1995).

Since, an urban drainage control model requires temporal variability processes, a recurrent neural network model is needed to model an optimal operation trajectory rather than achieve a static output. A proper neural network model for the urban drainage control is a nonlinear dynamic system using real-time recurrent neural networks. The Jordan network architecture is the selected architecture of the neural drainage module. The Jordan network is a neural network model with time-ordered or time-varying processes. This model has external and internal inputs. The feedback connections are the internal input of the model to provide a dynamic mode. The learning process in the Jordan network follows the standard back propagation algorithm (Freeman, 1994).

Most multi-layered neural networks include an input layer, at least one hidden layer and an output layer (Hyakin, 1994). Generally, the numbers of input and output neurons are determined based on the number of desired input and output variables. However, the selection of the number of hidden layers and the number of neurons in each layer is probably more of an art than a science. Each neuron of the input layer has a connection to every neuron of the hidden layer. Likewise, each neuron of the hidden layer should have a connection to every neuron of the output layer. In feed forward analysis of an ANN, nodes in input layer receive the inputs of the model and they flow through the network and produce outputs at nodes in the output layer (Neelakantan, et al., 2002). A weight in ANN is always associated with each connection to a neuron (Chang and Abdel-Ghaffar, 1992; Scalero and Tepedelenlioglu, 1992; Rasul and Paudyal, 1994).

In the real-time recurrent neural network model, the present outputs are also dependent on past outputs of the network. Thus, current errors may not only depend on the present parameter set, but also past parameter values (Srinivasan et al., 1994). Developing architecture and a learning algorithm are major problems with recurrent neural networks. Dependencies to past outputs are important items to be considered in the learning algorithm. The cost of computation, memory requirements and a simple set of rules are the advantages of using small networks. Usually, the analysis begins with a large size network, and then it is pruned to an appropriate size for particular problems. Sietsma and Dow (1988) explained a useful idea for pruning networks, but the technique for analysis was not successful in practice. This pruning technique uses the outputs of the hidden units as indicators for determining whether or not any units are contributing to the solution.

Karnin (1990) used the sensitivity of the error function to the exclusion of each synapse (connection), and then pruned the low sensitivity connections. In contrast, Chang and Abdel-Ghaffar (1992), and Hsu et al. (1995) begin with a small number of neurons and gradually increase the network size until the desired modeling accuracy is achieved. Many researchers use three layered neural networks because three layered neural networks are capable of approximating any continuous function to within an arbitrary accuracy (Takahashi, 1993; Ergezinger and Thomsen, 1995, Hsu et al., 1995).

2.6. Neural networks training

Two important steps in the neural network modeling process are the identification of the model structure, and the calibration of model parameters through an iterative procedure or a training process. The process training (also called learning) in neural networks involves adjusting or finding the optimum connection weights through many different ways. The goal of the training process in a neural network model is to choose the model parameters (connection weight). Minimizing the average sum-square error between the actual and desired output of the network is a general method to update the weights (Chang and Abdel-Ghaffar, 1992; Eberhart and Dobbins, 1990; Hegazy and Molsehi, 1994; Rasul and Paudyal, 1994, Hsu et al., 1995).

Unsupervised, supervised and reinforced learning are three basic ideas of learning in neural networks. Here, supervised learning is the proposed learning technique for this real-time recurrence neural network. A least-mean-square (LMS) or a delta rule is the common algorithm for finding the desired weights of this model. The LMS rule is the most applied simple learning rule for single and multiple unit neural nets. An error back-propagation algorithm or a gradient-decent search algorithm is an extension of the m-LMS rules. This technique is a highly popular algorithm with applications to pattern recognition, dynamic modeling, sensitivity analysis, and dynamic control systems. Error-correction in the learning rule of a back propagation algorithm is based on least-mean-square (Narendra and Parthasarathy, 1991; Werbos, P. J., 1990).

Currently, back propagation is the simplest traditional technique and the most popular technique for doing the supervised training task (Scalero and Tepedelenlioglu, 1992; Troll and Feiten, 1992; Rasul and Paudyal, 1994). Some researchers showed that the back propagation techniques have two major issues in the learning process. First, the learning algorithms may trap in a local minimum. A convergence rate in the learning process is another issue in the back propagation techniques (Chang and Abdel-Ghaffar, 1992; Scalero and Tepedelenlioglu, 1992). Using the steepest descent method in the back propagation technique is the simplest method of numerical optimization, but the calculation is not very efficient (Fletcher, 1987; Troll and Feiten, 1992). The characteristics of the objective function and dimensionality of the problem may also influence the difficulty to achieve a global optimal weight (Duan et al., 1993).

Many attempts have been made to improve the training process for neural network models by employing conjugate gradient methods, quasi-Newton methods, and a combination of both for improving the performance of the training process (Troll and Feiten, 1992). Chang and Abdel-Ghaffar (1992) introduced the gradient method with Armijos search. Scalero and Tepedelenlioglu (1992) introduced a new training algorithm that might be less sensitive to the initial weights and a rapidly converse setting. Baldi (1995) also reviewed the gradient descent learning technique and concluded that gradient descent can fail in several ways: by reaching a poor local minimum, encountering numerical precision problems, getting stuck in long plateaus, and by becoming prohibitive. Further improvements to make learning processes more efficient are still required. Ergezinger and Thomsen (1995) proposed a new learning algorithm that does not rely upon the evaluation of local gradients. This technique can speed up and increase the accuracy of learning algorithms for larger networks, and is a viable alternative for the urban storm water operational module.

III. NEURAL-OPTIMAL CONTROL MODEL

3.1. Overview

The neural-optimal control model for real-time regulation of combined sewer systems requires four modules; the rainfall-runoff module, the hydraulic routing module, the optimization module, and the dynamic neural control module. The rainfall-runoff module simulates inflow hydrographs from rainfall hyetograph data. This module is based on the RUNOFF block of the San Francisco storm water model as upgraded by Book (1980). The hydraulic routing module is the UNSTDY model originally developed by Chen (1973) and adapted by Book (1980) for branching storm-water drainage systems. The UNSTDY module provides a fully implicit numerical solution for the complete St. Venant equations in routing flows trough the storm sewer network. Chen and Chai (1991) updated the UNSTDY model to include several internal boundary conditions, branching pipe junctions, control gates and side channel overflows. A radial gate subroutine is added to determine gate openings for the real-time control model presented herein.

The optimization module utilizes an optimal control technique to maximize utilization of available inline storage in a storm water or combined sewer system and minimizes untreated overflows to the receiving waters. Inline storage refers to the temporary storage capabilities of large sewer pipes. An optimal control (OPTCON) model developed and described by Labadie (1993) is adopted as the optimization module for the real-time neural-optimal control model. Figure 3.1 illustrates the primary components of the real-time neural-optimal control model and interacting between the modules. According to the flow chart (Figure 3.1), off-line analysis is a process of estimating the weights as parameters of the neural control model. The model includes three major processes for preparing weights (parameters) of the neural control module in the online analysis of real-time neural-optimal control. The first off-line analysis process involves the rainfall-runoff simulation to determine the storm water hydrograph for the input of combined sewer networks. The second step is an iterative process between the hydraulic routing module and the optimization module to produce optimal policies or gate openings. The hydraulic routing (UNSTDY) module routes and analyzes storm sewer flows throughout the network and produces routing coefficients. The optimization module then evaluates the optimal gate openings from the system using the hydraulic routing coefficients computed from the UNSTDY model.

Since this result is an operating policy differing from the normal policy initially assumed in UNSTDY for producing routing coefficients, the UNSTDY model is again executed under the new operating policy, and the process repeated until it converges to consistent optimal policies for the system. In this step, the hydraulic routing module produces new or revised estimates of the routing coefficients and the state and control variables that constrain the optimization module.

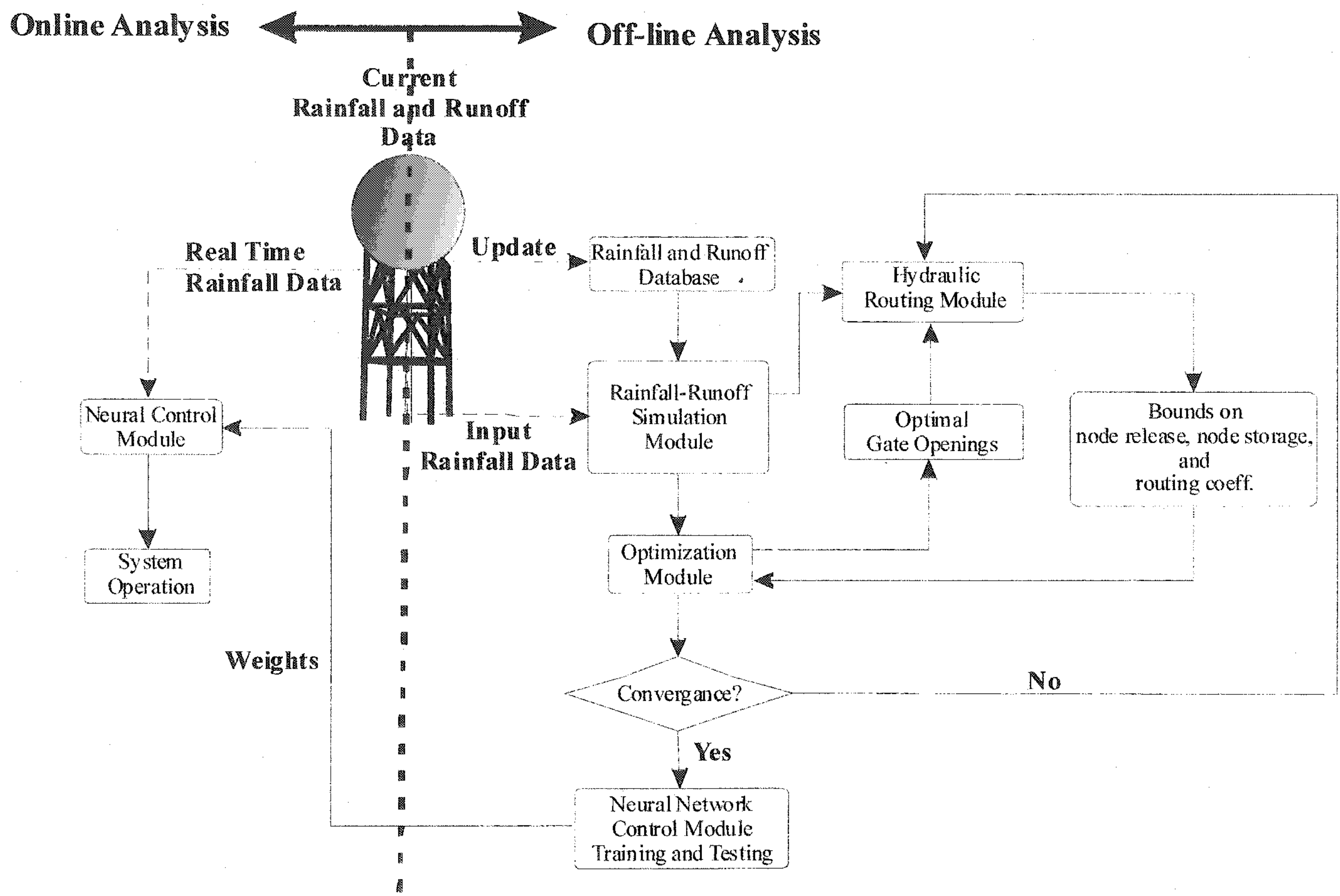

Figure 3. 1 Real-time operation and control system

Routing coefficients ($\{b_{ij}\}=\frac{u_{jt}^{k}}{u_{it}^{k}}$) are determined as the proportion of the sewer flow at the downstream pool storage and sewer flow at the upstream pool storage for the respective sewer reach at time t. (see Figure 3.2).

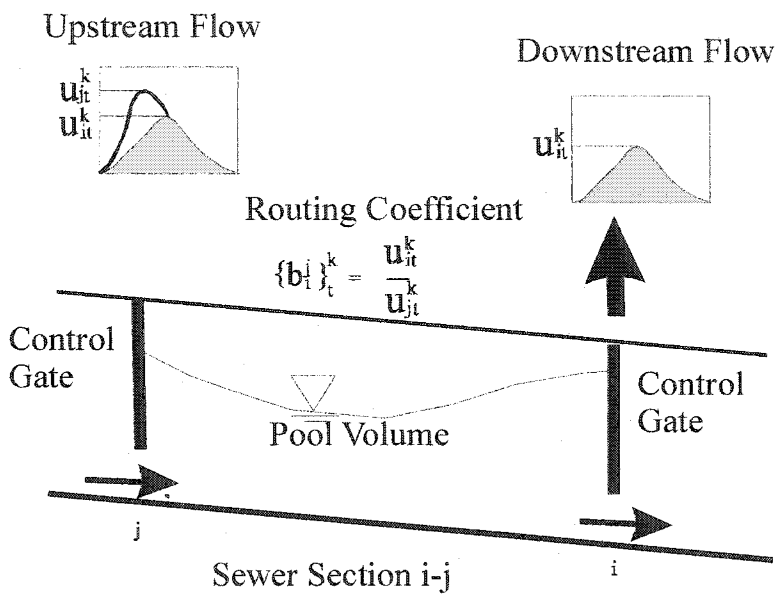

Figure 3. 2 Routing Coefficient

Solutions obtained from the optimal control module for a wide range of storm patterns provides the training data set for the artificial neural network model. The training process results in optimal weights. Finally, actual real-time operation employs the trained artificial neural network, but using inputs of real-time rainfall data. In this process, the neural-optimal control module evaluates optimal gate openings directly as the storm develops.

3.2. Rainfall-runoff simulation module

A modified San Francisco Storm Water Model is the parent of the rainfall-runoff module for the real-time combined sewer control model, because the model is a simple and a practical model for simulating inflow hydrographs. The model uses the kinematic wave technique to simulate overland flow. Recorded rainfall hyetographs from rain gauges in study area and surrounding areas are the primary input for the model. The combined sewer systems in large cities usually have dependable and reliable remote rainfall measuring devices, real-time sensors on sewer flows or sewer levels. In addition, measuring devices can transfer real-time data directly to the computer control system. Thus, analysis of real-time optimal operations using a neural-optimal control module based on historical rainfall data can be conducted prior to occurrence of the real flood event.

3.3. Hydraulic routing module

The purpose of the hydraulic routing module is to route flow throughout the system and compute routing coefficients and gate openings for every time step of the optimal combined sewer operation. Synthetic storm water hydrographs for each input point are generated using the rainfall-runoff module providing the main input to the hydraulic routing module. Since, this modified hydraulic routing model is able to route a flood hydrograph in an open channel under surcharge flow conditions, this model is an appropriate hydraulics module for the combined sewer real-time operation model. The full St, Venant equations are required to evaluate back water conditions caused by down stream control (Labadie, 1993). The full St. Venant equations are solved using an implicit numerical scheme. Upstream and downstream hydraulic boundaries are required to solve nonlinear hyperbolic partial differential equations of the St. Venant equations. The hydraulic routing model is also able to define the following boundary conditions:

1. Side channel overflows, which are calculated using the broad crested weir equation
2. Control gates using an orifice equation
3. Branching pipe junctions with up to three in-coming pipes and one out-going pipe

3.4. Optimal control module

The maximum utilization of available in-line or off-line detention storage is an inexpensive technique to reduce storm water flooding and the polluting effects of untreated spills to receiving waters (Labadie, 1993; Marinaki, et al., 1999). Thus, real-time control of a combined sewer system requires a real-time control computer model to determine an optimal regulation of gates, pumps or weirs operations. This computation should be based on a realistic assessment of current flows and storage in the system, as well as available real-time or direct storm information.

Reducing the occurrence of direct spills or reducing the pollution impact on receiving waters is the main goal of the combined sewer real-time control. Therefore, minimization of overflows and maximization flows to the waste water treatment plant are objectives of the combined sewer real-time control models. The following control parameters need to be considered in the models: selection of lead-time for anticipatory control and weighting factors for setting priorities on overflows in space and time. The control model is constructed to minimize untreated overflows from a storm water or combined system and minimize storage after the operational period (Labadie, 1993).

$$\text{Minimize } \sum_{t=1}^{T} f_t(x_t, u_t) + \Phi_{T+1}(x_{T+1}) \tag{3. 1}$$

Subject to $x_{t+1} = x_t + (B_t(u_t + u_{t-1})/2 + R_t)$. CONV; x_1 given

$x_{min} \lesssim x_{t+1} \lesssim x_{max}$

$u_{min} \lesssim u_{t+1} \lesssim u_{max}$ (for t = 1, ..., T)

Where:

x_t	=	node storage at the beginning of time interval t
u_t	=	node release rate at the end of time interval t
x_{max}, x_{min}	=	upper and lower bounds on node storage
u_{max}, u_{min}	=	upper and lower bounds on node release
R_t	=	storm inflows during period t
B_t	=	n x (m+n) matrix, accounting for attenuation and lagging of upstream releases to downstream nodes and system spills
CONV	=	conversion factors for converting average flow rates over period t to flow volume.

In this formulation, the hydraulic routing module of a drainage network will determine the bounds x_{max}, x_{min}, u_{max}, u_{min} and routing matrix B_t. The use of routing matrix B_t takes into account the routing of flow from upstream to downstream nodes and is determined according to the configuration of the system. Matrix element $\{b_{ij}\}$ has a positive numerical value if node i receives outflow from node j, or zero if the two nodes are unconnected. The state space constraints are expressed by the following expression ($x_{min} \le x_{t+1} \le x_{max}$). An augmented Lagrangian function is the simplest and most common method for dealing with this constraint. Thus, solution of the above optimal control problem requires determination of the set of Lagrange multipliers and admissible release trajectories that minimize the Lagrangian function. Simultaneous solution of a set of transversality, adjoint and stationarity conditions results in optimum values of u_t*.

The adjoint equations are nonlinear equations obtained by partial differentiation of the augmented Lagrangian function with respect to the state vector x_t. The stationarity conditions are similarly obtained by partial differentiation of the Lagrangian function with respect to the control vector u_t. Many optimal search techniques such as steepest decent method, the conjugate gradient method and quasi-Newton method can be used to solve these non linear equations simultaneously. To encourage minimization of over flows and maximization of flows to treatment plant, the following equation is a specific form of the objective function (Equation 3.2).

$$\text{Minimize} \sum_{t=1}^{T}\left[\sum_{i=1}^{m}\left(\left(p_{it}u_{it}^{2}\right)+w_{i}\left(x_{i,T+1}^{2}\right)\right)\right] \tag{3. 2}$$

where;

p_{it} = coefficients are used to set spill priorities over time and space.

W_i = weights assigned to encourage release of flood flows from storage.

The OPTCON model (Labadie, 1985) is the reference optimal control module to generate optimal gate openings as desired outputs in the training of the neural control module. The optimal control module uses the Potryagin Maximum principle to solve the general optimization problems. Labadie (1993) developed and modified the computer program for analyzing storm water management. The computer program requires determination of the set of Lagrange multipliers and admissible release trajectories that minimize the Lagrangian function. Therefore, the simultaneous solution of the set of transversality, adjoint and stationarity conditions, known as two-point boundary value problems (TPBVP), pertain to the minimization analysis. The adjoint equations are determined using partial differentiation of the Lagrangian function with respect to the state vector x_t. Partial differentiation of the Lagrangian function with respect to the control vector u_t is used to obtain the stationary conditions. Simultaneous solutions of nonlinear equations are the optimum values of u_t*.

The Fletcher-Reeves conjugate-gradient method is a suitable search technique to determine the control variables. This technique is chosen since it has the advantage of speed, robustness, and low computer memory requirements and it can be easily programmed. An initial guess on the control trajectory is required for estimating the Lagrange multipliers. In this analysis, an iterative process is repeated until the Lagrange multipliers and the control trajectories converge to their optimum values. The optimization, analysis is only needed for generating a training set of neural network.

The optimization process of the OPTCON module proceeds using the following steps. Subroutine state determines initial storages above the regulators using state equations for given storm water inflows. The program then evaluates the objective function, and penalty factors are added when the storage violates upper or lower bounds. The final step of the analysis is the optimization process. The transversality conditions are the initial backwards analysis of the adjoint equations in order to find the Lagrange multipliers.

1. The program computes the partial derivatives of the Lagrangian vectors with respect to the decision's vector. The program then determines the partial derivative of the Lagrangian function, with the gradient of the original objective function truncated, when the decision vectors violate the boundary conditions.

2. After the initial λ and the objectives are determined, then the conjugate gradients search process as the following algorithm in subroutine search.

. Set up the initial step sizes, this is used to define initial regions of uncertainty. The program starts to count the amount of times that is needed to expand the region of uncertainty. It is because solutions have been encountered on the arbitrarily specified boundaries of the uncertainty region. Calculate the new decision vectors, state variables and the objective functions along search direction and starting at the initial storage value. This step will evaluate new adjoint variables (i.e., Lagrange multipliers) and calculate a new gradient Lagrangian function using new decision vectors. The next process is evaluating the absolute difference between the previous and current objective values. The program will also check the counter of iteration still within the specified tolerance. If so, then repeat the analysis with the next set of penalties. Go to step eleven, when the total number of iterations exceed the maximum boundary.

3.5. Neural network control module

The first step in developing the neural dynamic network control module is identification of the architecture and structure of the model. This is followed by the learning and testing process using dynamic back propagation or other types of optimization algorithms. At the present time, the back propagation technique is the standard learning technique for multi layered neural networks. The final step is a model validation to test the weights or parameters of the tested model. Generally, a recurrent neural network model with three subsets (layers) of neurons is a good instrument to solve a nonlinear dynamic problem:

1. The input layer is composed of a series of input neurons. The input neurons receive external input information and transmit the input information to the hidden layer. The input layer in recurrent neural network models also receives internal information from the output layer of the model.

2. The output layer consists of series output neurons that receive processed information from the hidden layer and produces the network outputs. The network outputs of the recurrent neural network model are also utilized as internal input information of the input layer.

3. The hidden layer receives information from the input layer and supplies processed information to the output layer.

Figure 3.3 shows the general structure of a neural network control module to operate a real-time urban drainage control system where control decisions are dynamic and previous decisions may have influence on current decisions. Output from the hidden layer is computed in a forward step. The output layer then processes inputs from the hidden layer to determine the optimal gate openings. The main purpose of the dynamic neural control module is to compute the optimal real-time gate opening based on actual measured rainfall data and previous gate openings.

The weights are assigned to connect all neurons to other neurons on a different layer. These neurons communicate with each other only via weighted connections. The strength and the pattern of the weights mostly influence the response or the output of network. The neural control module needs a training or learning (or calibration) process to compute the optimal values of the weights.

The training process determines the parameters of the model, such as the number of the hidden neurons and the value of the weights for each connection. In addition, the module also requires a testing process to validate the parameters prior to actual application of the Jordan model. The Jordan model architecture with three layers of neurons is the selected architecture for the dynamic neural control module. Back-propagation with delta rule is the chosen technique to optimize the weights of the neural control module.

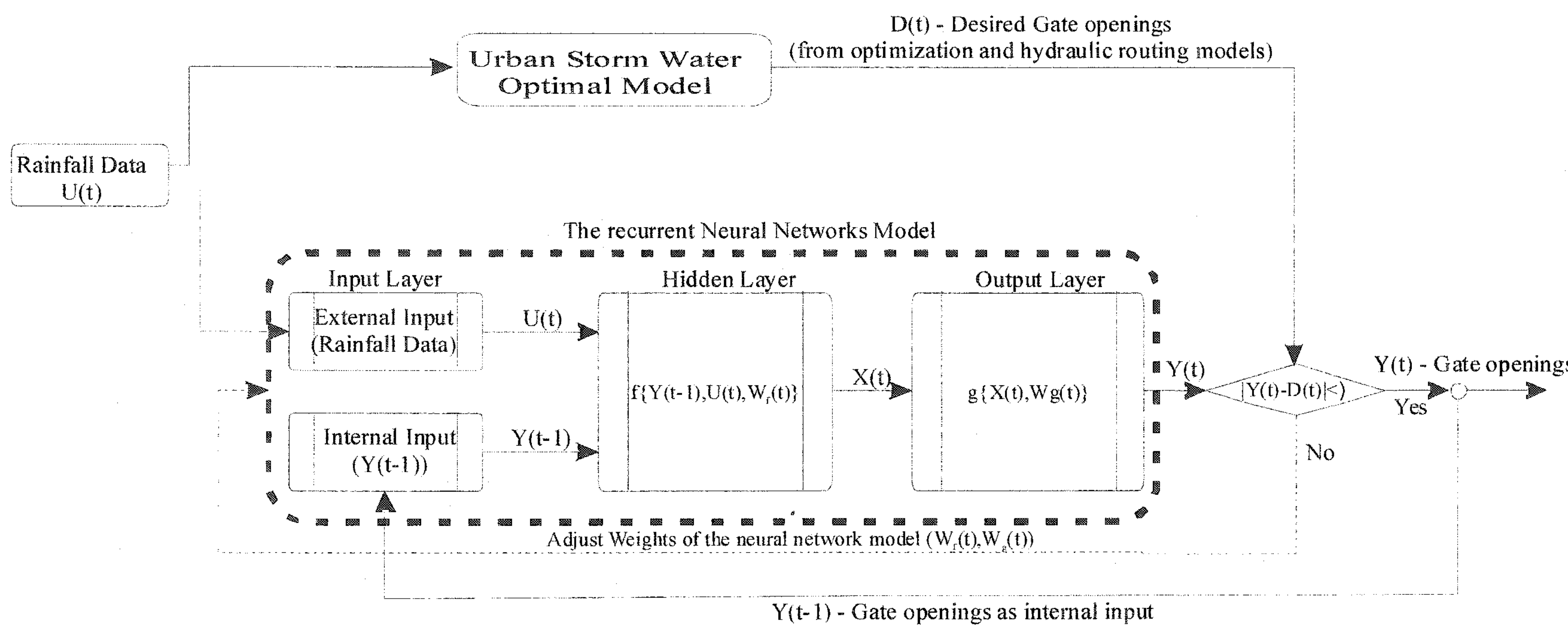

Figure 3. 3 Neural network control module

The external inputs to the ANN model are current rainfall data, lag one and lag two of spatially distributed rainfall data. In the case to facilitate smooth dynamic operation of the gates, the model also requires data of previous gate openings as the internal input. A trial and error process is used to evaluate the minimum square error (MSE) for determining the number of neurons on hidden layer. Since optimal of gates openings are the output of the module, the number of output neurons should be the same as the number of regulators in the system. The steps of the training process are as follows:

1. Calculate the number of connections between the input and hidden nodes, hidden and output nodes, and the total of all connections.

2. Initial weights are either determined using a uniform random number generator or alternatively, the initial weights can be read from a file and set for each connection.

3. Perform the back propagation analysis to calculate optimal weights using subroutine OPTWTS.

Learning or training of a neural network is primarily a process of adjusting values of the weights via various algorithms such as back-propagation or the delta rule. Back-propagation is a supervised error-correcting algorithm and it has demonstrated excellent capabilities to solve complex classification and prediction problems. A complete round of forwards and backwards processes, and weights adjustments using all input-output pair is called an epoch. According to the standard back-propagation analysis, the learning processes of the Jordan network are calculated using the following standard equations

(Hyakin, 1994, Freeman, 1994, Rumelhart and McClellan, 1986).

$$v_j^h(t)=\sum_{i=1}^{I} w_{ji}^h u_i(t)+\sum_{k=1}^{K} w_{ji}^h x_k(t-1)+\theta_j \tag{3. 3}$$

$$v_k^o(t)=\sum_{j=1}^{L} w_{kj}^o w_{kj} y_j(t)+\theta_k \tag{3. 4}$$

Where;

I = total number of external inputs applied to neurons on input layer.

K = total number of internal inputs originating from neurons of the output layer and applied to the remaining K neurons in the input layer.

L = total number of neurons in the hidden layer.

w_{ij}^h = the synaptic weight of connection of neuron (i) in the input layer to a neuron (j) in the hidden layer.

w_{kj}^o = the synaptic weight of connection of neuron (j) in the hidden layer to neuron (k) in the output layer.

$u_i(t)$ = the external input signal entering neuron (i) in the input layer at time t.

$x_k(t-1)$ = The one step delayed output vector from neuron (k) in the output layer, serving as the internal input to the input layer.

$x_k(t-1)$ = the output signal appearing at the hidden layer of neuron j

θ_j = the threshold input or bias unit that applied to neuron j (w_{ij} x bias input values for input layer)

θ_k = the threshold input or bias unit that applied to neuron k (w_{jk} x bias input value for hidden layer)

$v_j^h(t)$ = the net internal activity level of neuron j in the hidden layer

$v_k^0(t)$ = the net internal activity level of neuron k in the output layer

Activation of a back-propagation algorithm flows in one direction from the input layer to the output layer through the hidden layer. The equations below are the activation equations for calculating the output signal on hidden layer and output layer respectively.

$$y_j(t) = h_j\left(v_j^h(t)\right) \qquad j=1,\ldots\ldots,J \qquad (3.5)$$

and

$$x_k(t) = O_k\left(v_k^o(t)\right) \qquad k=1,\ldots\ldots,K \qquad (3.6)$$

The logistic function is a particular form of an activation function (f) that is commonly used in multilayer Perceptrons. The function is a bounded, monotonic, non-decreasing, and provides a graded, nonlinear response. According to the formulation of logistic function, the amplitude of the output lies inside the range $0 \leq y_k \leq 1$. (Hyakin, 1994, Freeman, 1994 and Govindaraju, 2000). Where, the following equation is a generalized logistic function;

$$x_i(t) = f_j\left(v_j(t)\right) = \frac{1}{1+\exp\left(-v_j(t)\right)} \qquad J=1,2,\ldots\ldots.N$$

The training process involves selections of optimal weights that minimize the following sum of square error function (Hyakin, 1994; Pineda, 1987; Pineda, 1988, Rumelhart and McClellan, 1986):

$$\xi(t)=\frac{1}{2}\sum_{k\in U} e_k^2(t)=\frac{1}{2}\sum_{k\in U}\left(d_k(t)-y_k(t)\right)^2 \qquad (3.7)$$

Where, $d_k(t)$ is the desired output on the output layer (gate openings that are obtained from OPTCON). $y_k(t)$ is the output of neural network model (from the output layer). Since the error function ξ depends on the synaptic weights of the network, the weights are dynamically adjusted using the following steepest descent procedure (Hyakin, 1994; Pineda, 1987; Pineda, 1988, Rumelhart and McClellan, 1986).

$$\Delta w_{ji}(t)=\eta\delta_j(t)y_i(t)+\alpha\Delta w_{ji}(t-1) \qquad (3.8)$$

with

$$\delta_k(t)=e_k(t)(f'_j(v_k)) \qquad \text{Neuron k is a hidden node} \qquad (3.9)$$

Where, η is the learning-rate parameter that determines the time scale over which the synaptic weights of the network change. The learning rate parameter η must be small enough to make these changes progress slowly or adiabatically with respect to the state equations. Parameter α is usually a positive number called the momentum constant. The derivative of activation function $f'_j(v_j(t))$ is used for estimating the local gradients of the output neuron k and the hidden neuron j. Eq. 3.10 is a local gradient equation for evaluating the output neuron gradient (Hyakin, 1994, Freeman, 1994, Rumelhart and McClellan, 1986). Since the hidden layer does not have target values (i.e. desired outputs) then the learning rule for the hidden layer is derived according to error back-propagation or the back propagate learning rule. This rule is an extension of the delta rule used to propagate the output errors ($d_k(t)$ - $y_k(t)$) backward through the output layer toward the hidden layer. Thus, the local gradient for evaluating the hidden neuron gradient is;

$$\delta_j(t) = f'_j\left(\upsilon_j(t)\right)\sum_k \delta_k(t) w_{kj}(t) \qquad \text{Neuron j is an output node} \qquad (3.10)$$

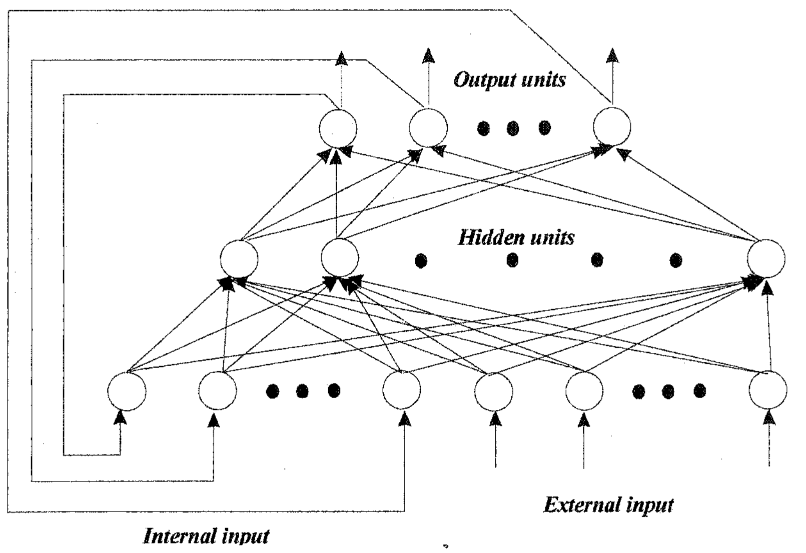

Figure 3. 4 Schematic of Jordan Architecture Networks

Figure 3.4 displays the structure of the three layered Jordan neural networks architecture as a recurrent neural network using the previous outputs as internal input. The first step in the training of this network is transformation of input-output data using standard normal formulation. Then, transform all input and output data using standard normal transformation technique. The primary purpose of data transformation is to normalize the input data to be between 0 and 1 because the activation function in the neural network can only produce output in the range between 0 and 1. An inverse transformation is required to change the output values from normalized outputs to the actual values of the gate openings. The next step is to generate the initial weights using a random number or to read a specific set of initial weights from a file.

The main part of this learning process is to proceeds systematic adjustment of the weights until a minimum error solution is found. Input values for each neuron in the hidden layer are cumulative products of the weight and input value of a neuron in the input layer (see Equation 3.3). According to Equation 3.4, the output value from each hidden neuron is the output of the activation function of the input value from each hidden layer. The mean square error is used as stopping criteria as part of forward calculations. The backward calculation evaluates the local gradient for neurons in the hidden layer and output layer, followed by calculation of the weight adjustment and the backward calculation is estimation of the new weights. This process continues until less than a specified tolerance, at which time the learning process is terminated (see Figure 3.5). Kramer and Sangiovanni-Vincentelli (1989) formulated a convergence criterion for back propagation learning as follows (Hyakin, 1995):

1. When the Euclidean norm of the gradient vector reaches a sufficiently small gradient threshold, it means the back propagation iteration already converged. However, this requires the computation of gradient vector g(w), where g(w) is the first-derivative of the error surface with respect to the weight vector w. The Euclidean norm of g(w) approaches as the optimal weights (w).

2. When the absolute rate of change in the mean square error per epoch is sufficiently small, it indicates the back propagation algorithm has converged. Typically, the rate of change is in the range of 0.1 to 1.0 percent per epoch.

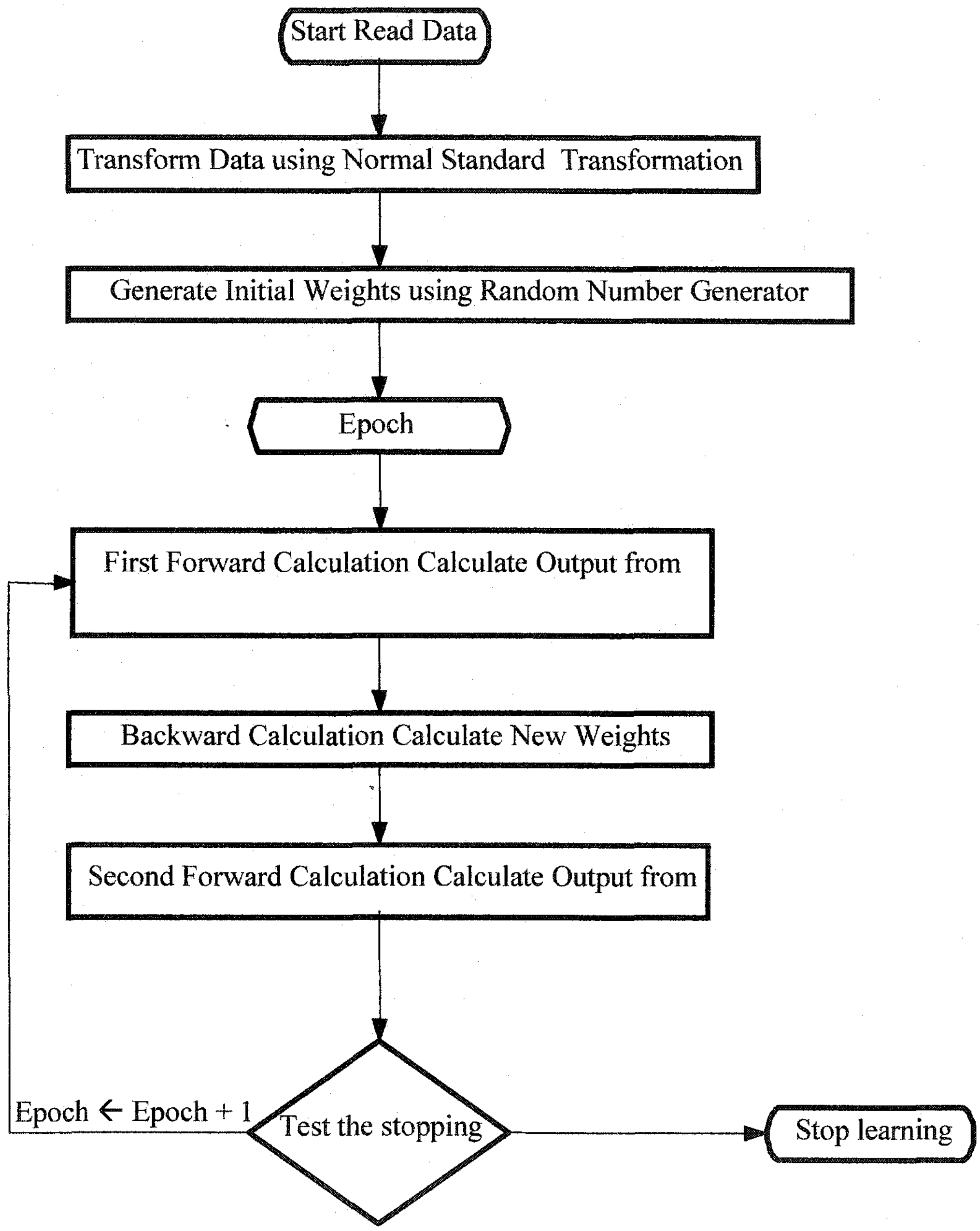

Figure 3.5 Learning process for dynamic neural network

IV. APPLICATION OF THE NEURAL-OPTIMAL CONTROL MODEL

4.1. Description of the study area

The combined sewer network for the West Point System of Metro Seattle Area is used for demonstrating the capabilities of the neural-optimal control algorithm. The sewerage system of Metro Seattle includes five wastewater treatment plants, with its own service area. The West Point and Alki plants are the only treatment plants receiving water from the combined sewer systems. In these systems, untreated overflows to Puget Sound may occur during storm periods. Both the West Point and Alki plants have large service areas, diverse and complicated systems. The catchments condition and drainage network data are taken from Brown and Caldwell report (1995). Although, some required updating data, they are sufficient for demonstrating the model application.

4.1.1 General condition of the study area

The West Point service area covers approximately 65,000 acres which includes 100 miles of gravity sewers, thirteen pumping stations and nineteen regulator stations. An automatic computer control system is capable for remote control operation of all regulator facilities. Figure 4.1 is the schematic of the west point tributary system with all inlet points, and showing the West Point treatment plant located on Puget Sound.

4.1.2 Hydrology condition of the study area

Precipitation data (in the form of rainfall hyetograph depth) for specified storm events are the primary input requirement for the rainfall-runoff module. The rain gauges are standard tipping bucket gauges with magnetic recorders and can record 0.01-inch of accumulated rainfall. Rainfall abstractions consist of infiltration through the ground surface, foliage interception, depression storage, evaporation and transpiration.

4.2. Analysis of the model

Calibration and validation are two important steps in the process for constructing a model. Model calibration is the process of adjusting and determining the parameters of the model to achieve an agreement between the model output and the measured or desired data. Validation is the process of model analysis to test the parameters that were estimated in the calibration process. Labadie (1993) showed that the hydraulic routing and the optimization modules are suitable and reliable for analyzing real-time urban storm water control of Metro Seattle. The hydraulic routing and optimization modules use storm sewer data from the previous study or some common references. The accuracy and applicability of the rainfall-runoff and hydraulic routing models have been proven for evaluating urban drainage networks and combined sewer systems by Labadie, et al. (1978) and Book(1980). The rainfall-runoff and hydraulic modules were also adjusted, calibrated and tested for Metro Seattle real time control model by City of Seattle Engineering Department (Vitasovic et al., 1990).

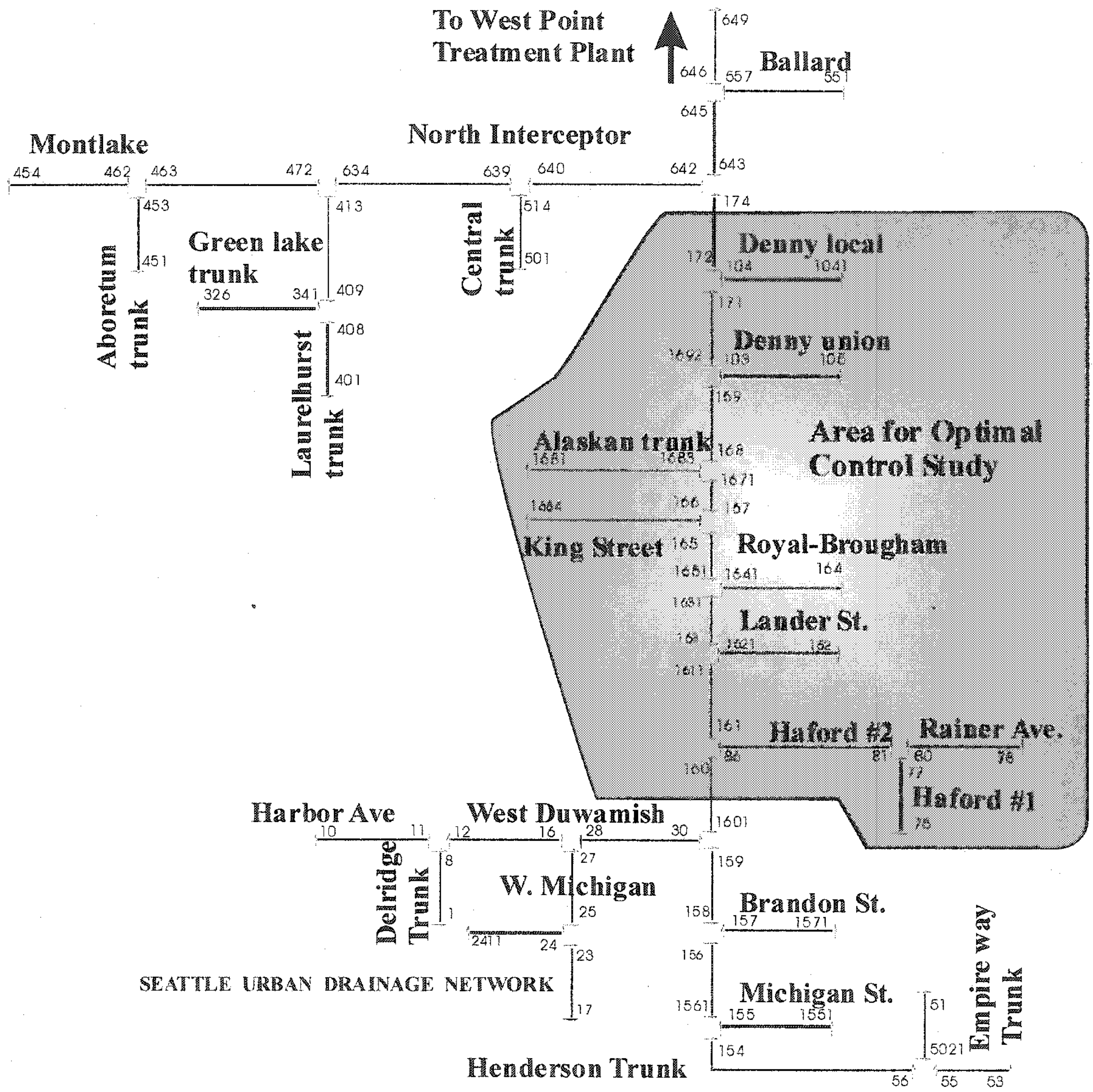

Figure 4.1 Urban drainage network for West Point System, Metro Seattle

4.2.1 Rainfall-runoff module

Effective rainfall in the rainfall-runoff module is the measured rainfall data minus infiltration and the depression storage of the Metro Seattle basin. The Metro Seattle land used will induce infiltration rate, imperviousness of the basin and sewage flow rate. The Horton equation is a selected infiltration model to estimate infiltration losses. Tables 4.1 and 4.2 are typical values of initial and final infiltration rates from a technical literature (Merril, 1985).

Table 4. 1 Infiltration rates by Land Use Classification, Cedar/Green River Basins (After Brown and Caldwell, 1985).

Land Use	Soil Intake Rate*	Infiltration rate (Inch/hour)**	
		Maximum	Minimum
Parks/dedicated open space	High	3.0	0.7
Agriculture	Medium	2.5	0.4
Unused land	Low	2.0	0.2
Single-family residential	High	2.5	0.4
	Medium	2.0	0.2
	Low	2.0	0.2
Multi-family residential	High	2.0	0.2
Commercial/services	Medium	2.0	0.2
Education, Industrial	Low	2.0	0.2

Notes: * From USDA Soil Conservation Service
** Decay rates of infiltration taken as 0.00115/second

Table 4.2 is also typical values of the infiltration rates which are taken from "Storm Water Management Model User's Manual", Version II."EPA-670/2-75-017, March, 1975.

Table 4. 2 Infiltration Rates, EPA-SWMM (After Merrill, 1985)

Classification	Infiltration rate (inches per hour)		
	Maximum	Minimum	Decay rate (sec^{-1})
Residential areas (standard curve)	3.0	0.52	0.00115
Industrial/commercial or Wet antecedent conditions (reduced curve)	3.0	0.30	0.0015
Sandy soil (high-rate curve)	5.0	0.7	0.0016

In addition to infiltration losses, depression storage is another required abstraction from rainfall. Generally, the estimated values of depression storage for the Seattle sub-catchments are 0.184-inch on pervious areas and 0.0625-inch or 0.1025-inch on impervious areas, depending on the average sub-basins slopes. Higher values would be appropriate for low slope areas which have parking lots and large flat-topped buildings, such as Ballard and Lander Street mostly are industrial areas (Brown and Caldwell, 1985). Validation of the rainfall-runoff module uses the model parameters from the Brown and Caldwell study. All parameters for rainfall-runoff module from the previous calibration and validation processes are used to test the agreement between observed and calculated base flow, peak flow, volume of hydrograph, and time to peak of hydrographs. The observed storm water flow hydrograph from inlet No.162 was taken as the measured storm water flow data. Figure 4.2 shows the comparison between the simulated and measured storm water flow hydrograph for inlet No. 162. Both simulated and measured inflow hydrograph have almost the same value of peak flow, base flow, volume of flow, and time to peak. Appendix II shows detail governing equations for the rainfall-runoff module.

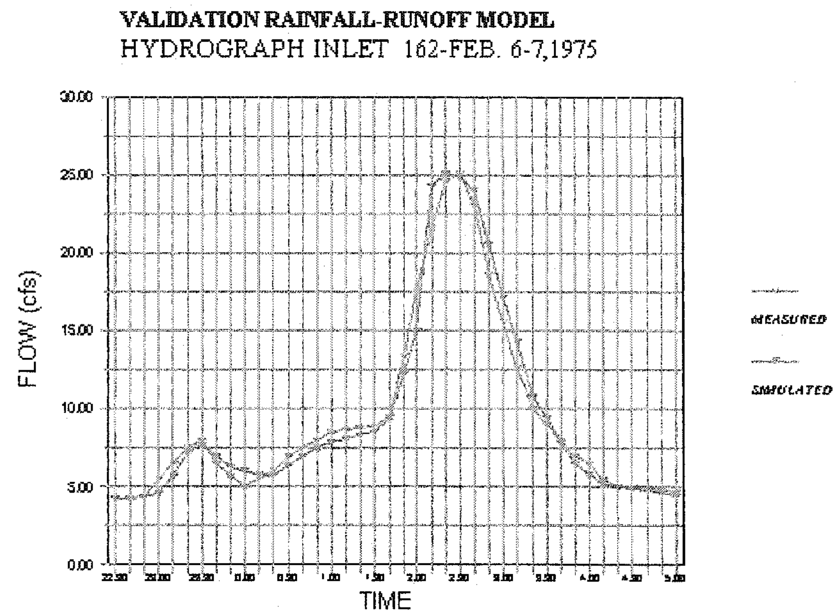

Figure4. 2 Example results of validation of rainfall-runoff module

4.2.2 Hydraulic routing module

The storm water hydrographs that are generated using the rainfall runoff module are then used as the inputs of hydraulic routing module. Pipe and gate sizes, pipe length, slopes and roughness coefficients, and junction data are also required by the hydraulic module. The hydraulic module routes the storm hydrographs along the sewer network, and the results are gate openings, attenuated storm hydrographs, and routings coefficients for optimization module. Appendix III highlights model algorithm for the hydraulic routing module. The attenuated storm hydrographs from storm event number 11 are shown in Figure 4.3 then are used as the input of optimization module for the study area.

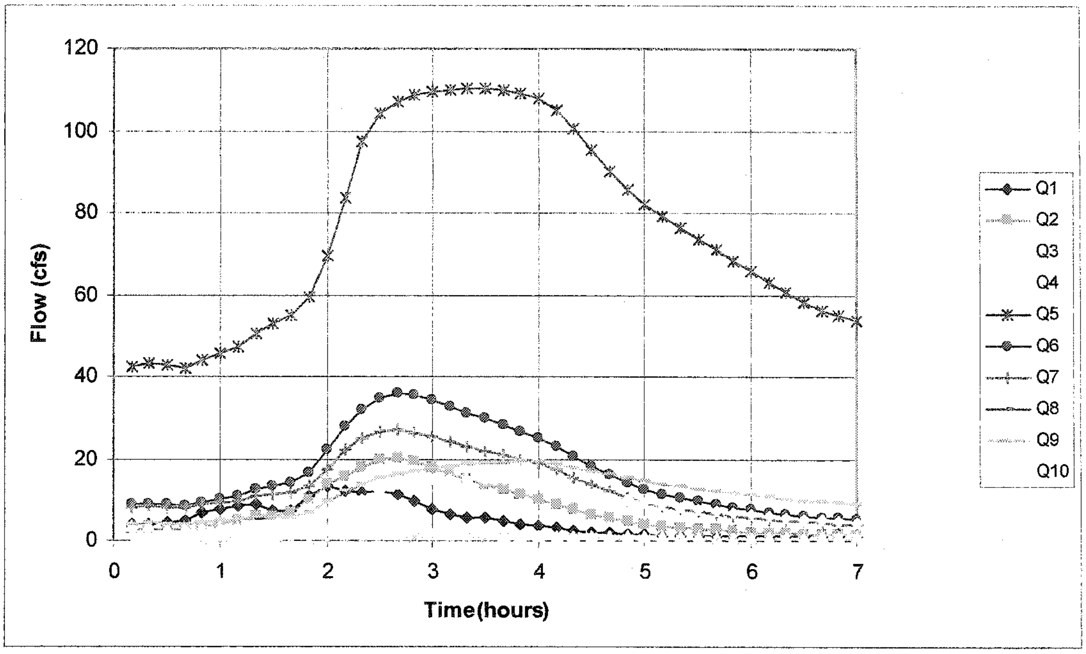

Figure 4. 3 Attenuated hydrographs from storm event number 11

Figure 4.4 is a schematic diagram of the study area of West Point Combined Sewer network. This area is a portion of the Elliott Bay drainage system, where it is automatically controlled to optimize in-system storage. The Rainfall-runoff module was utilized for predicting all inflows and lateral inflows for the West Point urban drainage network, followed by iterative analyses between the hydraulic routing module and optimal control module to determine the optimal gate control.

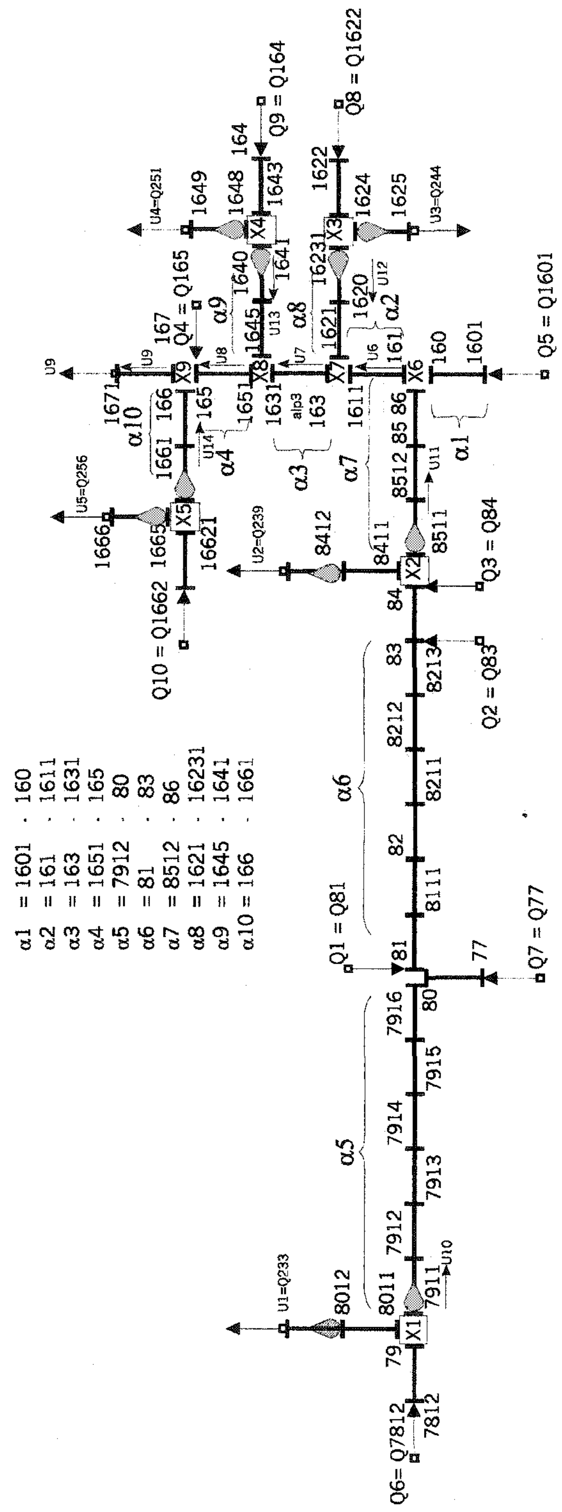

Figure4. 4 Schematic diagram of the drainage network of the West Point combined sewer system of Metro Seattle for demonstrating the model application.

4.2.3 Optimal Control module

Routing coefficients equal to 1.0 were used for the first initial approximations on routing coefficients of the iterative analysis. These values are subsequently updated by running the hydraulic routing module with updated control policies computed by the optimal control algorithm. The iterations are repeated until the routing coefficients converge to consistent values. Seven iterations are required to produce convergence of the routing coefficients. As shown in Figure 4.5.

Labadie (1993) demonstrated that $p_{it} = 0.1$ is a good objective function weighting factors to prioritize spills over time and space and the objective function weighting factor to encourage release after completion of the current storm event (w_i). A smaller ratio will increase the risk of giving insufficient weight to minimize overflow. On the other hand, a higher ratio has a tendency to maintain high storage to keep high storages at the end of the storm event and reduce the storm water release. Squaring the release rate variable in the objective function equation (see Eq.3.2) is intended to avoid rapid variation in gate operation. Figure 4.6 illustrates the results of the optimization module that maximize the use of storage in the combined sewer pipe to reduce untreated overflows from the storm event number 11. The model can reduce untreated overflows from storm event number 11. Figure 4.7 shows the total direct spills the CSS that are controlled using optimal control module and the total direct spill from uncontrolled CSS (All controlled gates are fully opened).

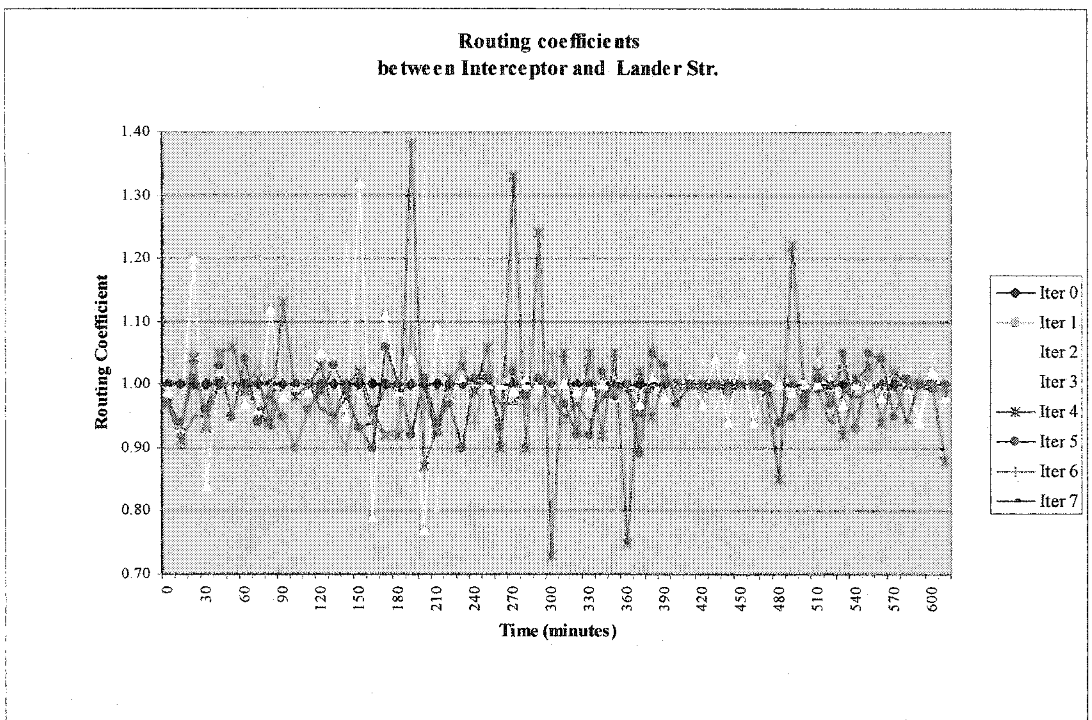

Figure 4. 5 Convergence of routing coefficients between Elliot Bay interceptor.

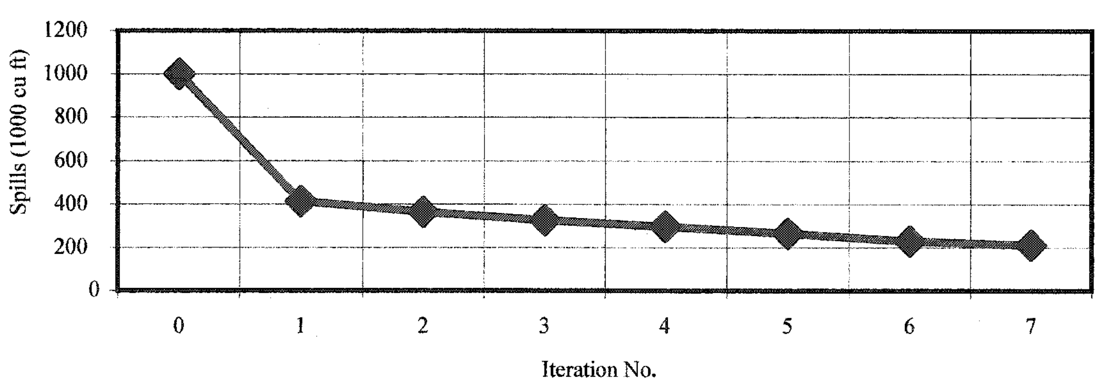

Figure 4. 6 Illustration of optimum use of in-system storage

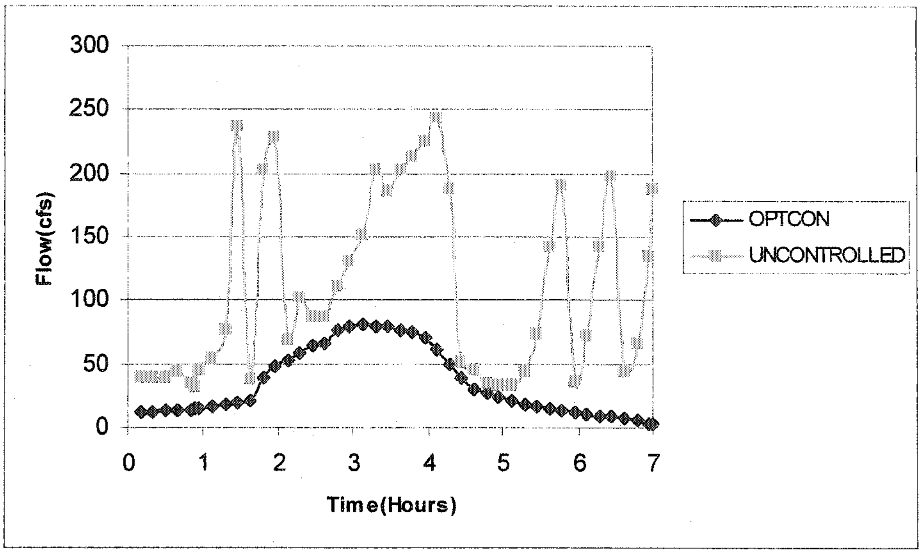

Figure 4. 7 Total direct spill from a controlled and an uncontrolled combined sewer system

4.2.4 Neural control module

The purpose of learning or training the process of the dynamic neural control module is to estimate the optimal model parameters (weights), as well as determining the optimum number of neurons in the hidden layer. The hydraulic routing and optimization modules evaluate the optimum gate openings which are then used as desired output values in the learning step of the dynamic neural control module. Rainfall hyetographs are external inputs of the module and the outputs from the previous time step are internal inputs. Optimal values of the learning parameter (η) and momentum constant (α) are based on experimental procedures to yield a minimum error.

Testing of the dynamic neural control module is a process of validating the model parameters from the learning or training step with input not included in the training set.

The input and output data sets for estimating parameters (i.e., training) should be different from the input and output data sets for validating the parameters (i.e., testing). Many statistical methods can measure and compare the performance of some neural network techniques and architectures.

4.3. Estimating model parameters

At the present time, heuristic and experimental procedures dominate selection of the optimal learning-rate parameter (η) and momentum constant (α). The values of η and α are optimal when these parameters can produce a minimum mean square error with the least number of epochs. Therefore, training experiments with combinations of learning-rate and momentum constants is still the best way to find the optimal parameters.

Figure 4.8 displays the experimental results of changing the momentum parameters α. The learning-rate (η) = 0.30 and, momentum constant (α) = 0.30 are optimal parameters of dynamic neural control module from the total epochs of training process = 90.

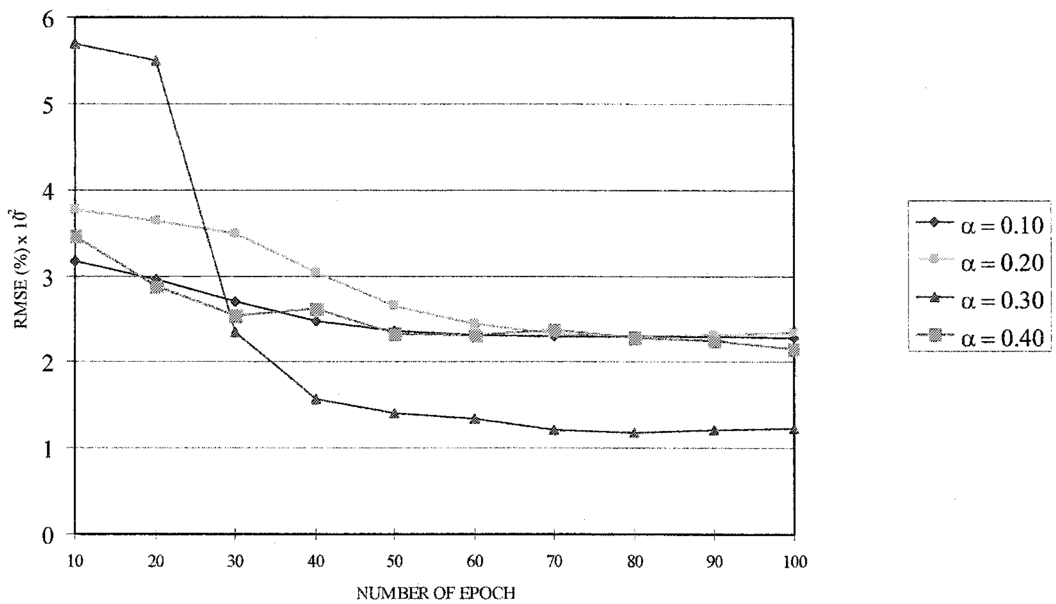

Figure 4.8 Results of experiments on the momentum parameter α

Masters (1993) recommends that the $\text{number of hidden neurons} = \sqrt{m\,n}$ for the networks with a single hidden layer, where n is the number of input neurons and m is the number of output neurons. This technique is only used to obtain a rough approximation of the ideal hidden layer size. An experimental approach was utilized to determine the optimal number of neurons in the hidden layer of the neural network model. Table 4.3, and Figure 4.9 show training sets associated with rainfall hyetographs event #1 through rainfall hyetographs event #10. Results indicate that 60 neurons and 50 epochs in the training process give the minimum value of RMSE.

Table 4. 3 Simulation results for evaluating hidden neurons

Number of epoch	Number of hidden neurons					
	10	20	30	40	50	60
10	0.000533	0.000503	0.000160	0.000136	0.000113	0.000040
20	0.000468	0.000421	0.000145	0.000089	0.000046	0.000027
30	0.000433	0.000374	0.000147	0.000073	0.000025	0.000021
40	0.000406	0.000338	0.000133	0.000071	0.000021	0.000021
50	0.000402	0.000303	0.000120	0.000072	0.000021	0.000024

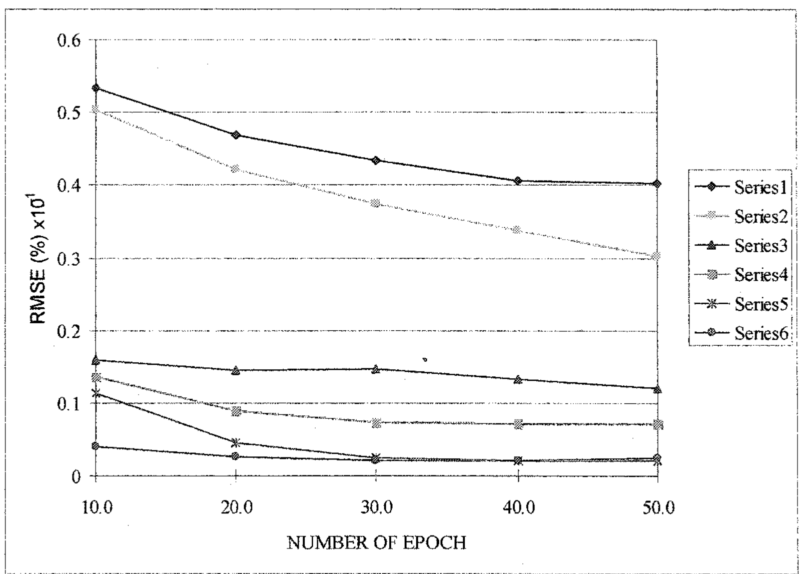

Figure 4.9 Optimal numbers of epoch and hidden neuron

4.4. Testing model parameters

Forty series of hyetograph rainfalls (Rainfall intensities are uniformly distributed for the entire basin) have been utilized to explore the possibility of applying dynamic neural network model as the real time control module. However, the dissertation needs to demonstrate the ability of the model to deal with rainfall data with spatial distribution data, such as rainfall hyetograph from radar. Therefore, the training and testing of the dynamic neural control module uses 11 series of synthetic rainfall hyetographs data from two stations as the inputs. The ten series of rainfall data is minimum number for training of the dynamic neural control module. Then, one set of storm events is used to test the model. Then, evaluate and plot all RMSE that come from those ten sets of parameters trough testing analyzes. The direct comparison between the outputs of neural control module and the desired outputs, and RMSE technique are two techniques used to test the parameters of the neural control module. The desired outputs are the optimal gate openings that are calculated using the optimal control module. The RMSE technique is a simple and a popular statistical technique for measuring performance of the learning process. It has several drawbacks such as a difficulty to distinguish between minor and serious errors (Masters, 1993).

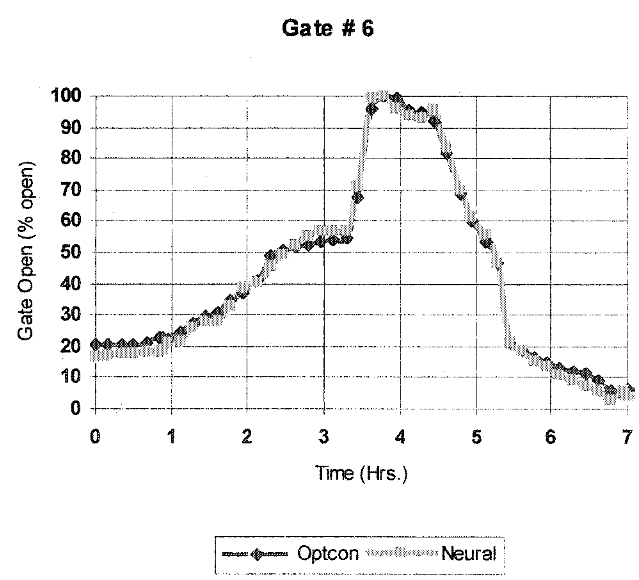

Figure 4. 10 Comparison between result of neural control and optimization module

Figure 4.10 is a chart of an operation pattern from gate no. 6 that derived from rainfall hyetograph event number 11. This chart illustrates that the output of the neural control model gives good agreement as compared to the output of the optimal control model. Thus, a dynamic neural control model is a simple new model for operating an urban drainage system. Figure 4.11 is a comparison between total direct overflow from the combined sewer system that was calculated using simulation and the neural control module for storm event number 11. The computing time required to find the solution (on PC-Pentium 4) may take 0.50 minutes for training of the neural control module, and 0.02 seconds for operating the neural control module.

Since, in a very short time, the model can produce gates operation pattern very similar compare to the operation pattern of the optimal control model, the application of the neural control model for a centralized real-time operation of the urban drainage networks is a reliable and feasible technique in reducing direct overflow of storm water.

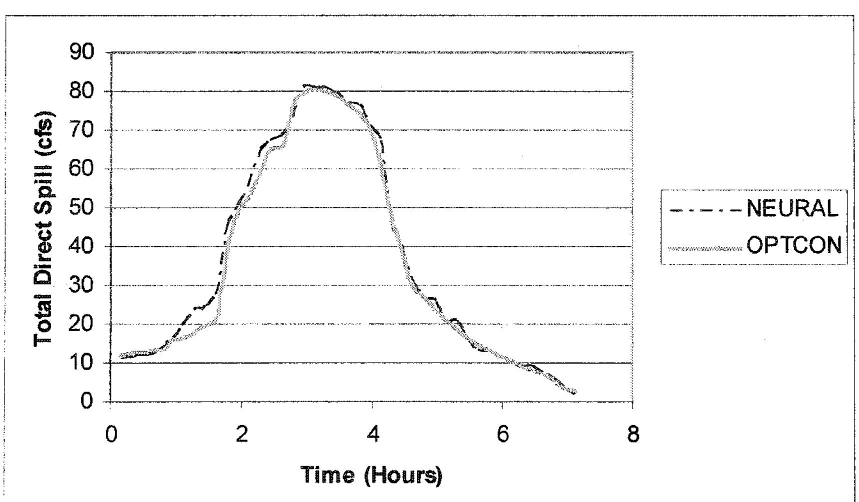

Figure 4.11 Comparison between result of neural-optimal control and optimization module for direct overflow.

V. CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusions

The following items are the conclusions of this dissertation, which are arranged based on the objectives of the dissertation:

1. The real-time control model has the capability to operate the combined urban drainage systems. As stated in the objectives of this dissertation, the real-time control model has four major modules with different purposes. The following items are the major purposes of the real-time control modules.

    a. The rainfall-runoff module is a hydrologic model that simulates inflow hydrographs for all input points.

    b. The optimization module is an optimal control theory model. The main purpose of the optimization module is to minimize the series of direct spills to a water body.

    c. The purpose of the hydraulic routing module is to route the flood and to analyze optimal gate openings based on inflow hydrographs and the optimal volume of direct spills. The optimal gate openings are used as the desired output in the learning process of the neural control module.

    d. The purpose of a dynamic neural network module is to determine directly the optimal control policies of the urban drainage system based on rainfall data.

2. Chapter III of the dissertation elaborates and reviews all general formulations for:

   a. The optimization processes using the optimal control theory.

   b. The processes training and testing in a dynamic neural-network model use back propagation technique.

3. The urban drainage operation needs a dynamic neural control model to control the gates. Jordan architecture is the structure of a dynamic neural network model for this neural control module. Even though the back propagation learning technique is a simple and a common technique in the area of neural network, this technique can produce good results for the dynamic neural network model. According to the inflow data, the optimization module produces the first decision of the optimal control strategy, according to the inflow data. After that, the hydraulic routing model will route the flow to update the routing coefficient and gates openings. It will then repeat the process until the results have converged. Based on rainfall hyetograph data and the weights, the neural control module can calculate the required gate openings during the drainage operations. The calibration and validation processes were only conducted to evaluate the parameters of the rainfall-runoff module and the neural control modules. The hydraulic routing module takes parameters of the module from some references, because the available data are not enough for calibrating and validating the parameters of the hydraulic routing module.

4. The following items are the primary contributions of the dissertation to the water resources and urban drainage operations:

   a. The three layers neural networks model with Jordan architecture is the model structure that can solve dynamic problems concerning water resources analyses. Back-propagation is a simple technique that is used to analyze the model parameters (weights). Performance of the real time control model will increase parallel to the increasing number of learning data.

   b. Dynamic neural network models can decrease the time required for analysis of real-time operations of the urban drainage system. However, it still needs to increase the model's precession and effectiveness of the learning process. The computer software still needs some improvements, because the decision support models need a user friendly and an iterative computer model. The software may need improvements by development of a visual drag-and-drop development.

   c. The neural network models may close the gap between the decision makers, the operators as the practitioners and the scientists. Since the practitioners do not like to use a method that requires high technical skills, the practitioners prefer to use charts or graphs as their tool for optimizing the real-time operation. The way that a neural control model analyses operating policies are similar to using a chart as an operating rule.

d. Chapter IV describes an application of this real-time control model for West Point System of the Metro Seattle Area. The application of the model shows that the neural control model has a simple analysis with similar results compared to results of the existing control model.

5.2. Recommendations

Learning techniques (such as optimization techniques) and optimal architectures are two major weaknesses for the present neural control module. Therefore, they become interesting topics for further research. The following items are recommendations for further studies on neural operation modules that are related to the water resources (urban drainage) systems:

1. An optimization method such as Conjugate-Gradient Method, Genetic Algorithm (GA) or Linear Least Squares Subplex (LLSSUB) may increase robustness of the learning technique.
2. Bertsekas and Tsitsiklis (1996) proposed Neuro-Dynamic Programming, where it may neglect the need of the optimization model such as dynamic programming or optimal control theory for producing the desired optimal control policies. This method aims to provide effectively sub-optimal solutions of planning and sequential decision making under uncertainty.
3. Since reservoir operations have similar ideas to the urban drainage operation, further propose researches may use the dynamic neural control module propose techniques for operating a series of reservoirs using the dynamic recurrent neural network

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APPENDIX I

OPERATION PATTERN OF CONTROL GATES

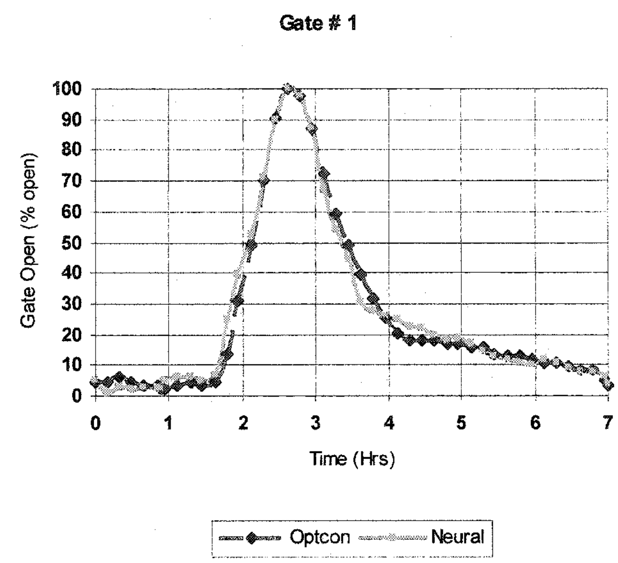

Figure 1 Operation pattern for gate # 1

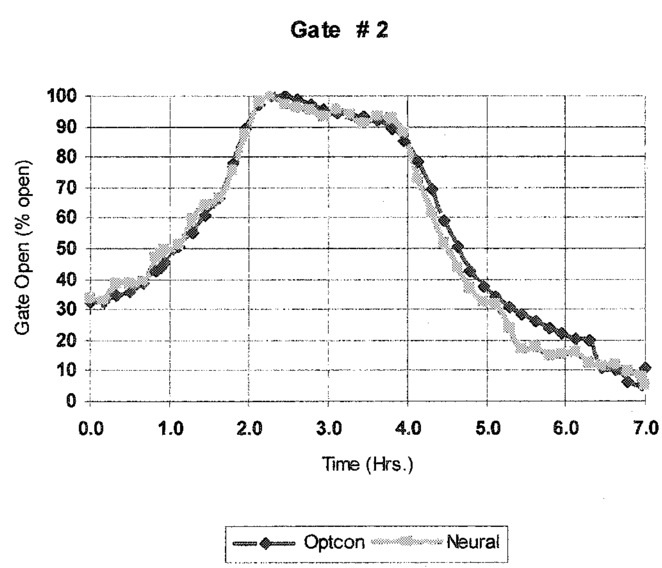

Figure 2 Operation pattern for gate # 2

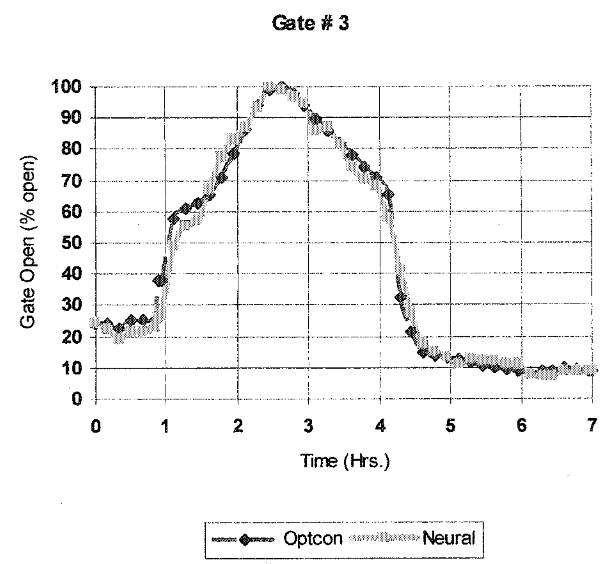

Figure 3 Operation pattern for gate # 3

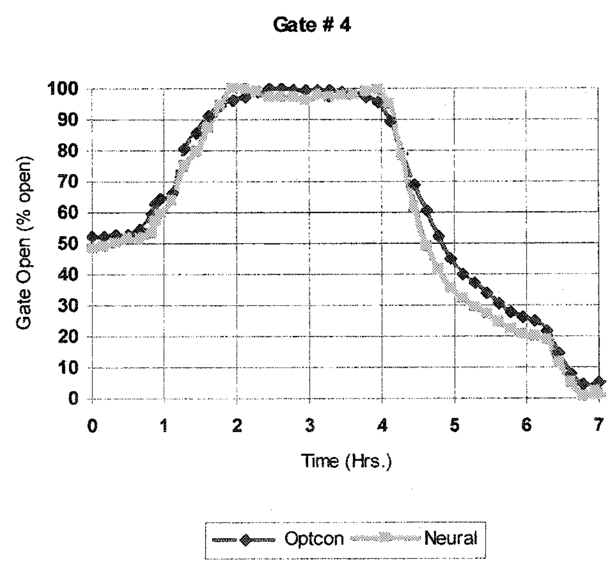

Figure 4 Operation pattern for gate # 4

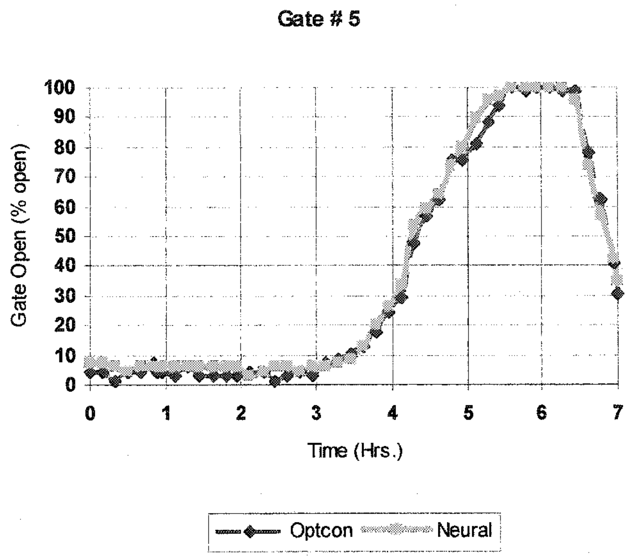

Figure 5 Operation pattern for gate # 5

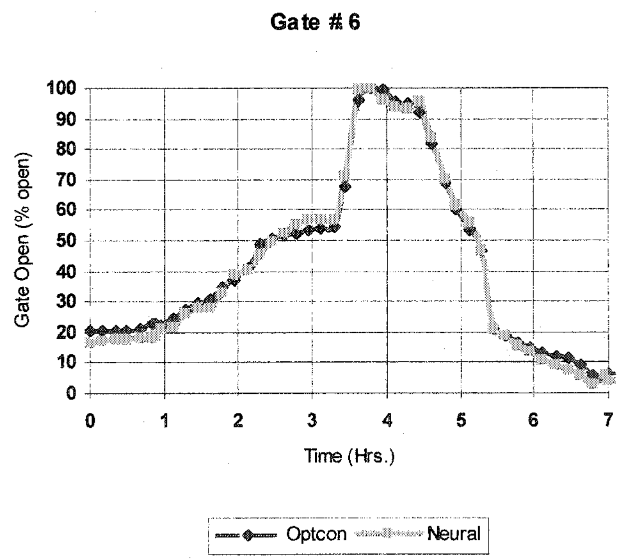

Figure 6 Operation pattern for gate # 6

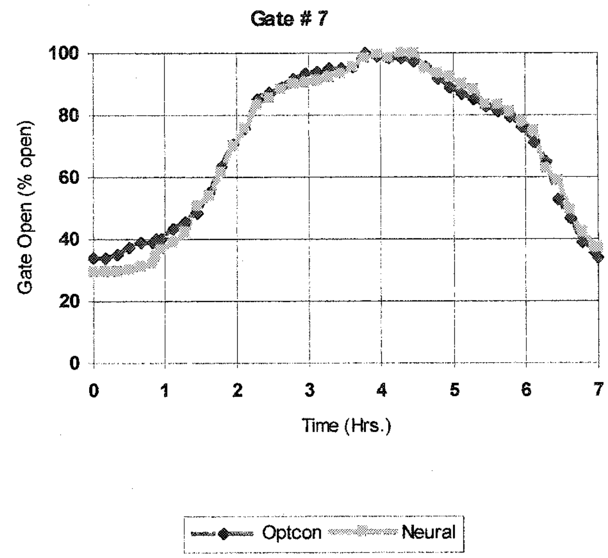

Figure 7 Operation pattern for gate # 7

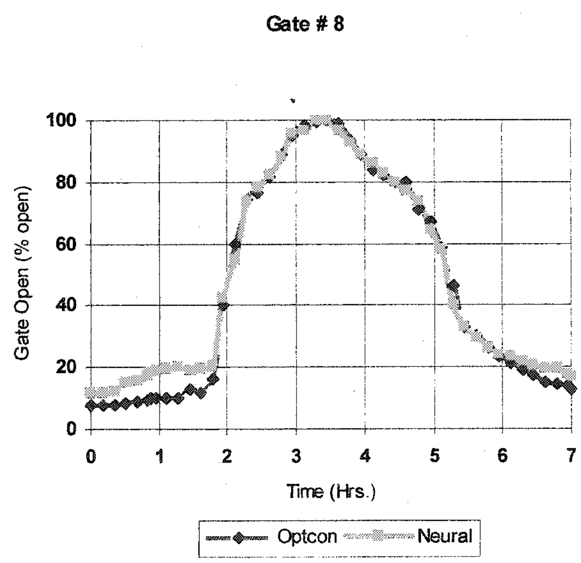

Figure 8 Operation pattern for gate # 8

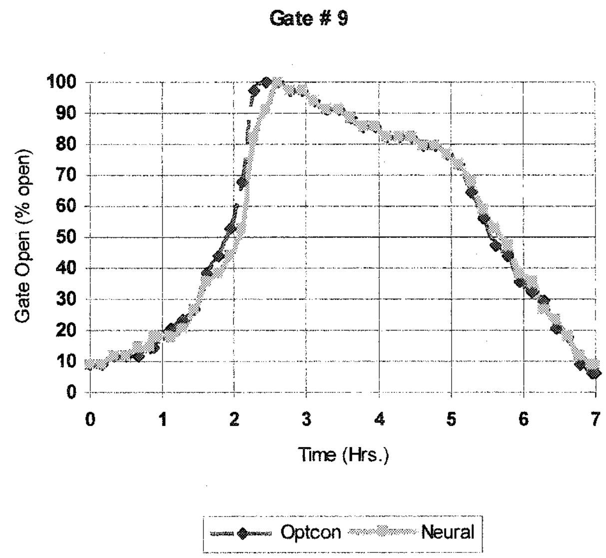

Figure 9 Operation pattern for gate # 9

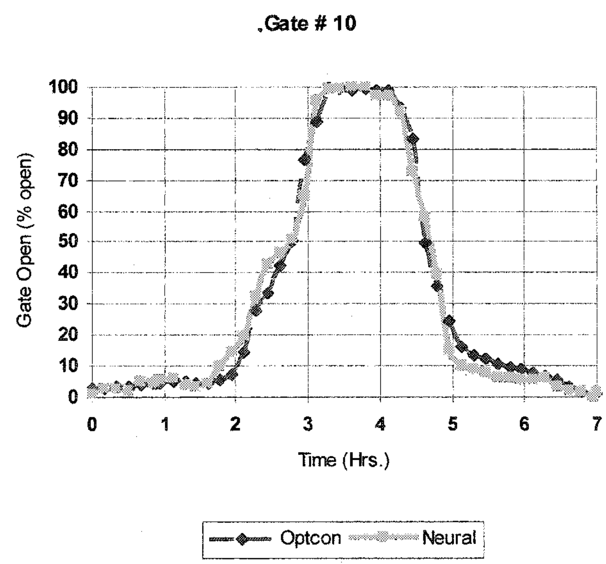

Figure 10 Operation pattern for gate # 10

APPENDIX II

RAINFALL-RUNOFF MODULE

A CSS real-time model needs actual rainfall and a runoff module to simulate a runoff hydrograph from a hyetograph rainfall record. The rainfall-runoff module was modified from The San Francisco Storm-water Model (SFSM), because the model is a simple model. It was developed essentially for urban areas (Book, 1980). Kinematic wave approximation is the technique used to determine runoff from urban drainage basins. Various analyses in the model are analyses of overland flow, water loses (infiltration losses and depression storage), and minor sewers flow. The rainfall hyetograph, slope, area and width of drainage basins are inputs of the module. The overland flow length is an implicit input that is calculated from the value of the area divided by the width of the plain (Book,1980). Hydraulic roughness and imperviousness are other important inputs.

The kinematic wave approximation is an adequate technique to route effective rainfalls (that term for the result of rainfalls minus the losses) across the urban basins and the minor sewers. An explicit finite difference formulation was adopted to solve the flow equations. In the kinematic wave approximation, the friction slope is assumed equal to the bed slope, and the friction slope is approximated using the Manning equations. A Newton-Raphson iterative technique is the method to solve the flow equations simultaneously. A sub-basin is a partition of an urban basin that has a relatively uniform characteristic.

Infiltration losses and depression storage are two important losses that are considered in this rainfall-runoff model. This rainfall-runoff model uses either the Horton or Green Ampt method to estimate infiltration losses (Book, 1980, Labadie, 1993). Trapezoidal, triangular, rectangular, circular pipes and parabolic channels are five channel shapes considered for surface flood routing in the rainfall-runoff sub model. The parabolic channel is the most important shape of gutters, because this shape is the best shape to approximate the small and medium size of natural channel.

Overland flow is storm water flow over surfaces, such as lawns, street pavements, sidewalks, until the flow reaches a gutter. The shapes of most drainage areas are very complex, but they can be simplified for modeling purposes (Akan, 1993). The ideal shape of sub-basins is a rectangular shape and has uniform slope in a direction perpendicular to the width. However, most sub-basins do not have a rectangular in shape with properties of symmetry and uniformity. The sub-basins width may influence the time of concentration and the shape of the hydrograph. The width of a sub-basin is approximately equal to the length of the channel for a sub-basin with drainage gutter in one side. DiGiano and Mangarella (1977) presented a simple way to handle a sub-basin that has a center gutter channel and an irregular shape. Figure II.1 and Equation II.1 show a skew factor that is used to solve the length problem of sub-catchment with a center gutter (Huber and Dickinson, 1988).

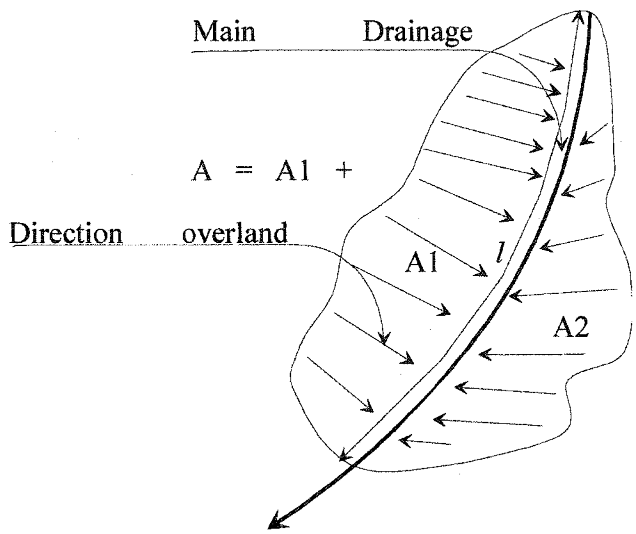

Figure II. 1 Width for irregular sub-catchment (after DiGiano et al., 1977)

$$S_k = \frac{(A_2 - A_1)}{\bar{A}} \qquad \text{(II. 1)}$$

Where;	S_k	=	a Skew factor, $0 \leqq S_k \leqq 1$,
	A_1	=	area to one side of channels,
	A_2	=	area to other side of channels,
	A	=	the total area,
	w	=	the sub-basin width,
	l	=	the length of main drainage channel.

$$l = \frac{(2 - s_k)}{w} \qquad \text{(II. 2)}$$

The following expression is the one-dimensional continuity equation with lateral inflow for a unit width of plane (Yevjevich, 1975; Book, 1980; Choi, 1991).

$$\frac{\partial d}{\partial t}+\frac{\partial(ud)}{\partial x}=q_l \qquad \text{(II. 3)}$$

Where; d = the depth of flow,

u = an average velocity,

q_l = the lateral inflow.

Multiplying the numerator and denominator of $\frac{\partial(\mathrm{ud})}{\partial \mathrm{x}}$ by plane width and expanding gives (Book, 1980).

$$\frac{d_1-d_2}{\Delta_t}-\frac{Q_1-Q_0}{\Delta_s}=R-I \qquad \text{(II. 4)}$$

Where; d_0 = the depth at time t,

d_1 = the depth at time t+Δt,

Q_0 = average outflow from plane during Δt,

Q_1 = inflow to the area from upstream sub-catchment,

Δs = surface area of the sub-catchment,

R = rainfall intensity during Δt,

I = infiltration rate during Δt.

An important assumption in the kinematic wave approximation is the energy line parallel to the bed slope, thus, (Muzik,1981; Stephenson,1981). The following expressions are the continuity equation and momentum equation for the kinematic wave approximation (Akan and Yen, 1980; Muzik 1980; Stephenson, 1981).

$$\frac{1}{g}\frac{\partial(u)}{\partial t}+u\frac{\partial(u)}{\partial x}+\frac{\partial d}{\partial x}=S_0-S_f \qquad \text{(II. 5)}$$

Where; g = gravitational acceleration,

S_o = a bottom slope,

S_f = a friction slope.

The Manning equation below is the equation for approximating the value of friction slopes.

$$Q_0 = \frac{K}{n} A R^{2/3} S_0^{1/2} \qquad \text{(II . 6)}$$

Where, Q_o is sub-basin outflow, n is Manning roughness coefficient, A is flow area, R is hydraulic radius, K is 1.486 for U.S. custom and 1 for SI units.

The flow depth (d) is an approximation parameter of the hydraulic radius (R), because the width (w) of an overland flow is very large compare to the flow depth (d). Flow area for an overland flow is equal to (Wd). Thus, the manning equation became the following expression:

$$Q_0 = \frac{K}{n} W \left[\frac{(d_0 - d_1}{2} \right]^{5/3} S_0^{1/2} \qquad \text{(II . 7)}$$

Where, d_o is the water depth, d_s is the depth of depression (retention) storage and W is the width of the sub-catchment.

Equation II.4 and Equation II.7 are two equations with two unknown parameters (Q_o and d_1) that should be solved. A Newton-Raphson iteration technique is an appropriate technique for solving those equations simultaneously. However, these two equations need a new arrangement and combination before the analysis is performed (Book, 1980).

$$F = \Delta d - \Delta t(k_n.\overline{Y}^{5/3} + R_e) \qquad \text{(II.8)}$$

Where; F = Newton's function driven to zero,

Δd = $d_1 - d_o$

K_n = $-(1.486/n\ S_o^{1/2}\ W) / A_s$

$\overline{y}$ = $(d_o + d_1)/2 - d_s$

= $d_o - d_s + \Delta d/2$

Re = $(R - f) + Q_i / A_s$

The following expression is differentiation of equation II.8;

$$\frac{dF}{d(\Delta d)} = 1 - \Delta t \frac{5}{6} K_n \overline{Y}^{2/3} \qquad \text{(II. 9)}$$

The iteration process is a technique to approximate the value of Δd, and the following equation is the equation for approximating the value of Δd in the iteration:

$$(\Delta d)_{n+1} = (\Delta d)_n - \frac{F_n}{\left[\dfrac{dF_n}{d(\Delta d)}\right]} \qquad \text{(II.10)}$$

Where, n and n+1 is iteration sequence. The iteration is stoped when the value of F approaches zero, then the values of Δd, d_1 and Q_o can be determined.

Surface roughness and vegetation types on the surface of sub-catchments are important factors for estimating the hydraulic Manning roughness coefficient (n). Model calibration or actual observation of the sub-catchment area is the way for estimating the value of n. Table II.1 gives typical values of the hydraulic Manning roughness coefficient (n) for overland flow. Either the Horton's or the Green Ampt equation is the infiltration model to estimate the losses in the rainfall-runoff module. The following formula is the Horton's infiltration model.

Table II. 1 Manning values for overland flow (after Book, 1980)

SURFACE*	Manning's n	SURFACE**	Manning's n
Concrete or Asphalt	0.010 – 0.013	Smooth Asphalt	0.012
Bare Sand	0.010 – 0.016	Asphalt or Concrete	0.014
Graveled Surface	0.012 – 0.030	Packed Clay	0.030
Bare Clay-loam Soil	0.012 – 0.033	Light Turf	0.200
Sparse Vegetation	0.053 – 0.130	Dense Turf	0.350
Short Grass Prairie	0.100 – 0.200		
Blue Grass Sod	0.170 – 0.480		

*** Wollhiser(1975)**
**** Water Resources Engineer, Inc. (1974)**

$$f_p = f_c + (f_0 - f_c).e^{-kt} \qquad \text{(II. 11)}$$

Where: f_p = the infiltration capacity into soil (l/t),

f_c = the minimum or ultimate value of f_p,

f_o = the maximum or initial value of f_p,

t = time from beginning of storm,

k = a decays coefficient.

Table II. 2 The range values of f_c (after Musgrave, 1955)

Hydrological Soil Group	f_c (m/hr)
A	0.45 – 0.30
B	0.30 – 0.15
C	0.15 – 0.05
D	0.05 – 0.00

The parameter f_c is essentially equal to the saturated hydraulic conductivity K_s, which is called "permeability." There are four hydrologic soil groups according to the U.S. soil conservation service (SCS). The value of infiltration capacities (f_c) can be determined based on the hydrology soil group (see Table II.2). Musgrave (1955) explained the range values of f_c for each hydrological group (Huber and Dickinson, 1988).

Book (1980) explained that the disadvantage of the Horton's model is the infiltration rate only depends on the time and availability of water. How much water has already infiltrated may not affect the infiltration rate. Another problem will occur to this model when more than two periods of low or zero intensity rainfall separate two events of high intensity rainfall. Horton's infiltration rate continues to decay although infiltration may not occur.

The Green-Ampt equation, formulated by Mein and Larson in 1973 is an alternate infiltration model for estimating infiltration. Therefore, the user may compute either the infiltration using the Horton's or the Green-Ampt model. There are two steps in the analysis of infiltration using the Green Ampt infiltration model. The first step is process to predict the volume of infiltration before the surface becomes saturated. The second step is the prediction of infiltration capacity. Therefore, the following equation is the equation for estimating infiltration capacity (Enggert, 1976).

$$f = kc\left(1 + \frac{\alpha}{F}\right) \qquad \text{(II. 12)}$$

Where, f is the infiltration rate, F is the infiltration volume, kc is the hydraulic conductivity and α is the potential head parameter. This equation is a non-linear and implicit with respect to time. It may be applicable for conditions of surface pounding. The following expression is the equation for evaluating the infiltrated volume.

$$\Delta F = \frac{-(2F(t) - k_w \Delta t)}{2} + \frac{\left[(2F(t) - k_w \Delta t)^2 + 8k_w \Delta t(\alpha + Ft)\right]^{1/2}}{2} \qquad \text{(II. 13)}$$

Where, ΔF is an infiltrated volume during period Δt, F(t) is a cumulative infiltrated volume at time t, and k_w is the hydraulic conductivity in the wetted zone. K_w and α are the two parameters of the Green-Ampt equation. Hydraulic conductivity in the wetted zone (k_w) can be approximated as one-half the saturated hydraulic conductivity. Displacing all of the air from the porous soil during infiltration time is usually impossible. Beside that, the following equation is a formulation for estimating α.

$$\alpha = \Phi\Psi(S_w - S_1) \qquad \text{(II. 14)}$$

Where, Φ is porosity of soil, Ψ is a suction head, S_W is the final degree of saturation and S_i the initial degree of saturation. Table II.3 and II.4 presents the value for hydraulic conductivity and section head for various soil types.

Table II. 3 Permeability (hydraulic conductivity) classes* (after Book, 1980).
(From USDA Soil Conservation Service Permeability Tests)

Class	Rate (in/hr)	Representative Soil Type
Very slow	< 0.06	Clay
Slow	0.06 – 0.20	Silty Clay
Moderate Slow	0.20 - 0.63	Silty Clay Loam
Moderate	0.63 - 2.00	Silty Loam
Rapid	2.00 - 6.30	Sandy Loam
Very Rapid	> 6.30	Sand and Gravel

The values of hydraulic conductivities in this table are the values for saturated hydraulic conductivities. Thus, to represent the conductivity in the wetted zone, they must be divided by two.

Table II. 4 Average capillary suction for selected types of soil (after Enggert, 1976)

Soil Type	Range of Average Capillary Suction (Inches)
Nickel gravel-sand loam	2.0 - 4.5
Ida silt loam	2.0 - 3.5
Poudre fine sand	2.0 - 4.5
Plain field sand	3.5 - 5.0
Yolo light clay	5.5 - 10.0
Colombia sandy loam	8.0 - 9.5
Guelph loam	8.0 - 13.0
Muren fine clay	15.0 - 20.0

APPENDIX III

HYDRAULIC ROUTING MODULE

The purpose of THE hydraulic routing module (UNSTDY model) is to route storm water hydrographs through the combined sewer networks, junctions and control structures to the treatment plant. A one-dimensional hydrodynamic numerical model is the primary tool to solve unsteady flow in combined sewer and storm water sewer networks. Numerical stability, computational accuracy, capabilities and robustness in handling complicated hydraulic conditions are required in the hydraulic routing module. The dynamic nature of an urban sewer system is often apparent because of the rapid changes due to the nature of rain events or the cycling of pumps. Free surface flows are most hydraulic flow conditions in sewer pipes, therefore the Saint-Venant's equations for one-dimensional unsteady flow in non-prismatic channels or conduits are the basic equations for analyzing unsteady sewer flows. According to the one-dimensional phenomenON, the conservation mass momentum, and the energy equation are the basic equations in developing the governing equations (Chen and Chai, 1991; Ji, 1998).

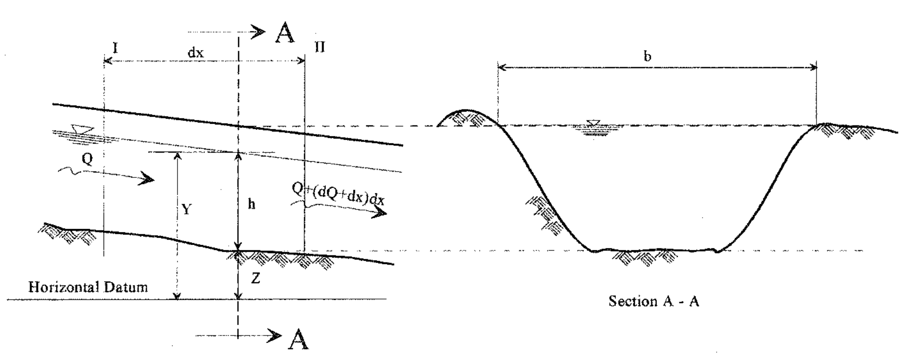

Figure III. 1 Schematic of open channel reaches

$$\frac{\partial A}{\partial t} + \frac{\partial Q}{\partial x} = q_l \qquad \text{(III.1)}$$

$$\frac{\partial(\rho Q)}{\partial t} + \frac{\partial(\rho Q V)}{\partial x} + \rho g A \frac{\partial h}{\partial x} + \rho g A (S_o - S_f) = 0 \qquad \text{(III.2)}$$

Where;

A is flow cross sectional area,

Q	=	discharge,
V	=	velocity,
q_l	=	lateral flow per unit length of the channel or conduit,
x	=	longitudinal distance,
t	=	time,
S_o	=	bed slope of channel or conduit,
S_f	=	friction head loss slope,
g	=	gravitational acceleration.

Due to the complexity of the complete unsteady flow equations, the hydraulic routing module requires numerical schemes to simulate the storm water flow. Explicit and implicit schemes are two types of numerical schemes to solve the complete unsteady flow equations. Researchers have proved that the implicit scheme is the most stable, faster and most accurate compare to other finite-difference methods for floods routing in open channels (Amein and Fang, 1970; Price, 1974; Choi, 1991; Chen and Chai, 1991). Four-point implicit scheme presented by Preissman in 1960 is adopted as the numerical scheme for the UNSTDY model.

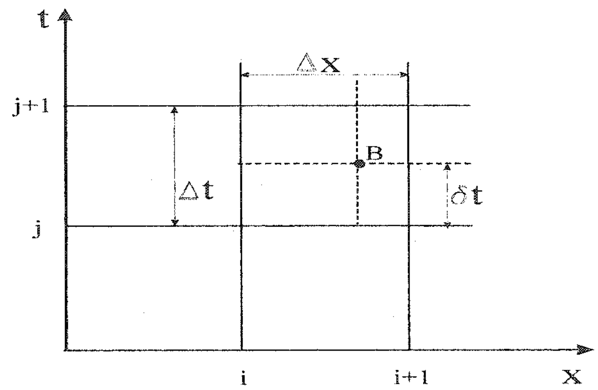

Figure III. 2 Computational grid of four point numerical scheme

In this scheme, the following equations are used to approximate functions f(x.t), derivative for depth $\frac{\partial f}{\partial x}$ and derivative for discharge $\frac{\partial f}{\partial t}$:

$$f(x,t) = \lambda \frac{\Delta f_i + \Delta f_{i+1}}{2} + \frac{f_i^j + f_{i+1}^j}{2} \tag{III. 3}$$

$$\frac{\partial f}{\partial x} = \lambda \frac{\Delta f_i + \Delta f_{i+1}}{\Delta x} + \frac{f_i^j + f_{i+1}^j}{\Delta x} \tag{III. 4}$$

$$\frac{\partial f}{\partial t} = \frac{\Delta f_i + \Delta f_{i+1}}{2\Delta t} \tag{III. 5}$$

where;

$$\Delta f_i = f_i^{j+1} - f_i^j \text{ and } \lambda = \frac{\delta t}{\Delta t}$$

λ is used to locate point B on the dashed line and adds flexibility to the scheme. The scheme is called center implicit when λ=1, and the scheme is explicit if λ=0. The fully implicit scheme was adopted for this model to avoid stability problems. The double sweep technique that was introduced by Fread (1971) is adopted to solve a matrix of linear implicit equations simultaneously.

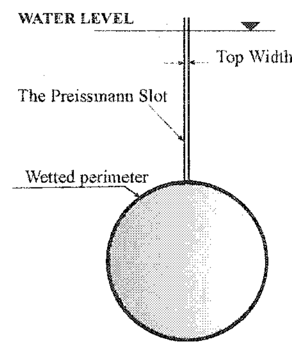

Figure III. 3 A hypothetical slot at the top of a pressurized sewer

A Preissmann Slot based technique allows to evaluate unsteady flow in a storm sewer network for submerged condition. A hypothetical slot at the top of the pipe as depicted in Figure III.3 can attain much larger pressurized flow wave celerity, thus the same set of unsteady flow equations can be applied to solve a surcharge flow condition. The width of the slot in the present model is assumed to be 0.1% of the maximum width of a conduit under surcharging condition. Normally the upstream boundary of the hydraulic routing module is a discharge hydrograph, and the following ways are used to determine the downstream conditions.

Discharge hydrograph, Q(t)

Stage hydrograph, y(t)

Stage-discharge rating curve, $Q = a\,y^b$

Rating table of Q vs y

Storage basin.

The hydraulic routing module could handle a branch sewer network using a dendritic system of junctions with two or three inflow branches and one outflow pipe (see Figure 3.3). The hydraulic equations for sewer flow through a confluence junction are the continuity and energy equations (Chen, 1979).

$$Q_1 + Q_2 + Q_4 + Q_{lat} = Q_3 + \frac{\partial V_o}{\partial t} \qquad \text{(III. 6)}$$

$$\left(H_1 + \frac{V_1^2}{2g} = H_3 + \frac{V_3^2}{2g} + h_{f1} \right)^{j+1} \qquad \text{(III.7)}$$

$$\left(H_2 + \frac{V_2^2}{2g} = H_3 + \frac{V_3^2}{2g} + h_{f2} \right)^{j+1} \qquad \text{(III.8)}$$

$$\left(H_2 + \frac{V_2^2}{2g} = H_3 + \frac{V_3^2}{2g} + h_{f2} \right)^{j+1} \qquad \text{(III.9)}$$

Where: V_o = volume

Q_{lat} = lateral discharge into junction

h_f = energy loss through junction

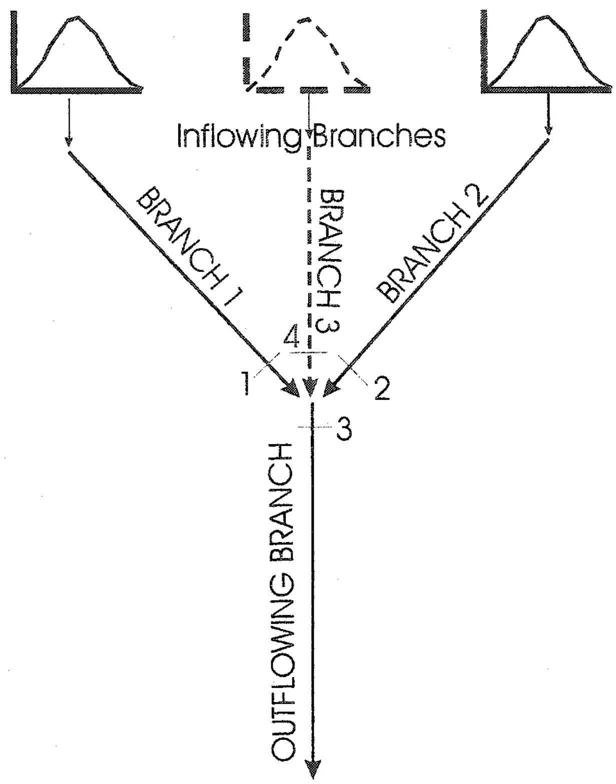

Figure III.4 Schematic of converging channel junction

The real time operation of urban drainage networks need in line or off-line storage for detaining storm flood hydrograph from the upstream areas. Therefore, control devices are required to regulate in line and off-line storage of storm water flow. The seven different control devices included in the hydraulic routing module are weirs, sluice gates, radial gates, siphons, orifices, and storage facilities.

A. Weirs

The purpose of diversion weirs is for diverting flow during periods of storm runoff. The following expression is the equation used to compute flow over the weir (Roesner, et al., 1988; Chen and Chai, 1991).

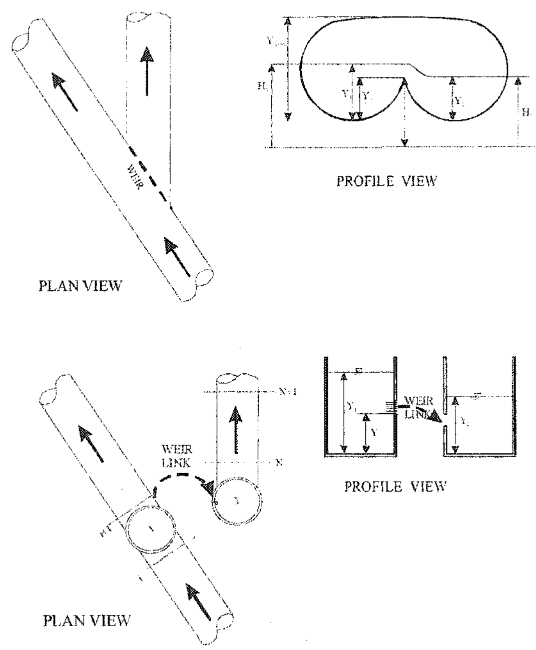

Figure III.5 Schematic of diversion weir (after Chen and Chai, 1991)

$$Q_w = -C_w L_w \left[(H_1 - Z_s) \sqrt{2g(H_1 - H_2)} \right] \qquad \text{(III.10)}$$

Where, C_W = the discharge coefficient,

L_W = weir length (transverse to overflow),

Y_1 = the water depth in the upstream side of the weir;

Y = the water depth in the downstream side of the weir;

Y_c = the height of the weir crest.

Equation III.10 is applicable if $H_1 \geqslant H_2$ and Q_w with negative value the overflow is an outflow. When H_2 is lower than Z_s then equation III.10 is modified to equation III.11.

$$Q_w = -C_w L_w \left[\sqrt{2g(H_1 - H_2)}^3 \right] \tag{III.11}$$

When $H_2 > H_1$ then flow becames an inflow then the proper equation for computing flow over the weir is Equation 3.25. The discharge coefficient (C_w) is the coefficient used to represent the reduction in driving head and all other variables. The equation is the weir equation from Roessert's Handbook of Hydraulics (Roesner, et al, 1988).

$$Q_w = -C_w L_w \left| (H_2 - Z_s) \sqrt{2g(H_1 - H_2)} \right| \tag{III.12}$$

B. Sluice Gate

The uses of control gates are to control in-line or off-line storage and to control release water. The gate sluice equation was chosen to estimate the flow based on the gate opening and the change in stages. The following expressions are the gate equations (Chen and Chai, 1991; Morrow, 1978).

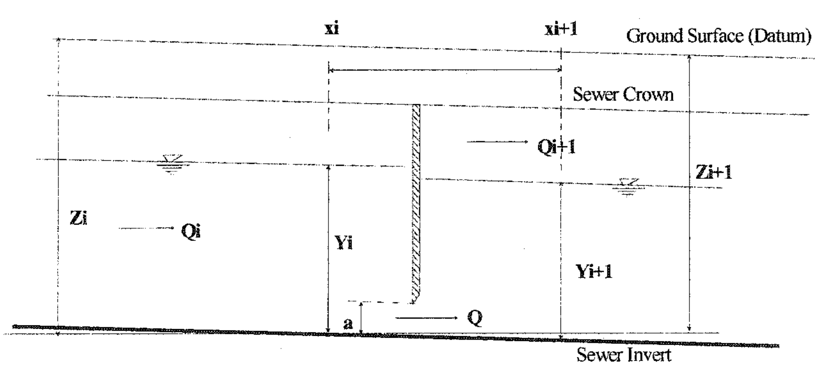

Figure III.6 Schematic diagram of a sluice gate

$$Q_i = K_g f(a)\sqrt{2g|Y_i - Y_{i+1}|} \qquad \text{(III.13)}$$

Where; K_g = 0.75,

$f(a)$ = flow area under the gates = a * b,

b = width of the gate,

a = gate opening,

Y = depth of water.

C. Radial gates

Radial gates are other discharge control structures for a wide range application in urban drainage systems. Discharge characteristics are dependent on the specific geometry of the gate such as the angle and design of the gate lip. Figure III.7 shows a typical model of radial gates. The following expression is the equation for estimating the discharge through a radial gate.

$$(Q_g) = -C_g L_g Y_g \left[\sqrt{2g(Y_i)}\right] \qquad \text{(III.14)}$$

Where; C_g is the discharge coefficient, L_g is the gate width, and Y_i is the upstream head.

U.S. Bureau of Reclamation developed a series of algorithms to estimate discharge coefficients for radial gates over a wide range of gate geometry and operating conditions (Chen and Chai, 1991; Buyalski, 1983). James and Young (1989) incorporated these algorithms into SWMM. The UNSTDY model also adopts this algorithm to evaluate the flow through radial gates. When flow in the free flow condition, the discharge coefficient varies with Y_g and Y_1. However, it becomes a function of Y_g, Y_1, and Y_2 when the flow is submerged flow.

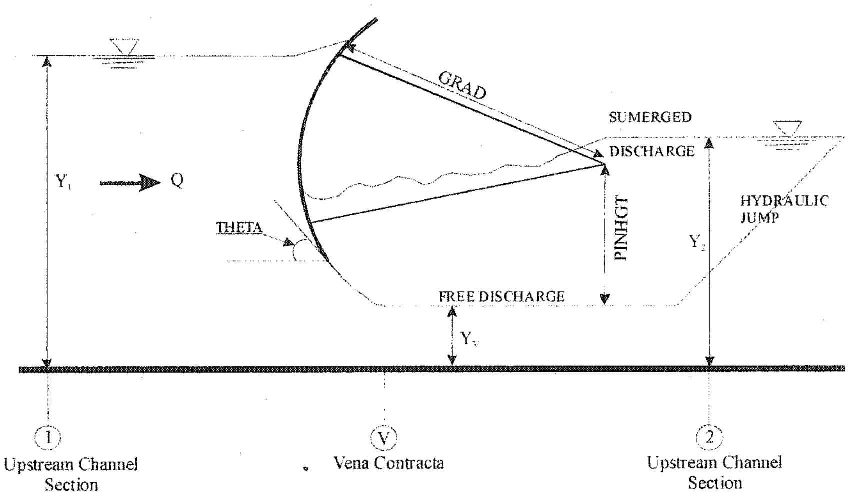

Figure III.7 Schematic diagram of a radial gate

D. Siphons

The hydraulic routing module can handle inverted siphons and siphon weir. Invert siphon can analyzed as regular pipe segments, and siphon weirs are similar to overflow weirs that have been described previously. The following equations are used to determine capacity of a siphon in prime condition.

When a siphon is prime and if $h_1 \geq h_2$, then $Q_S = -C_S A_S \sqrt{2g(h_1 - h_2)}$

When a siphon is prime and if $h_1 \geq h_2$, then $Q_S = -C_S A_S \sqrt{2g(h_2 - h_1)}$

Where, C_s is the discharge coefficient, A_s is the siphon area, h_1 is the head immediately upstream of the siphon and h_2 is the head immediately down stream of the siphon. If a siphon is not primed, then the flow becomes a weir flow. Therefore, the capacity of the siphon can be determined using the weir equation.

E. Orifice

The orifices generally can be utilized to divert storm water to another pipe, a pump station or storage tank/basin. The hydraulic module can handle two types of orifices: (overflow) orifices and in-line orifices. The solution procedures of side orifices are very similar compared to overflow weir analysis. The orifices have circular cross sections while overflow weirs have rectangular cross sections.

F. Pump Station

Wet-well pumps and dynamic head pumps are two types of pump that can be included in hydraulic routing analysis of the module. A pump station can have multiple pumps, and each pump has its own pump rule. The total pump rate is determined using the following equation.

$$Q_p = \Sigma_k P_K$$

Where, P_k is the pump rate for a given depth, k is number of pump.

G. Storage Basins

In-line and off-line storage basins are used to detain storm water flow from the upstream areas. Figure III.8 shows a conceptual representation of in-line and off-line storage basins. In-line storage basins can be treated the same as regular computational points, and an off-line storage basin is simulated using depth vs surface-area relationships.

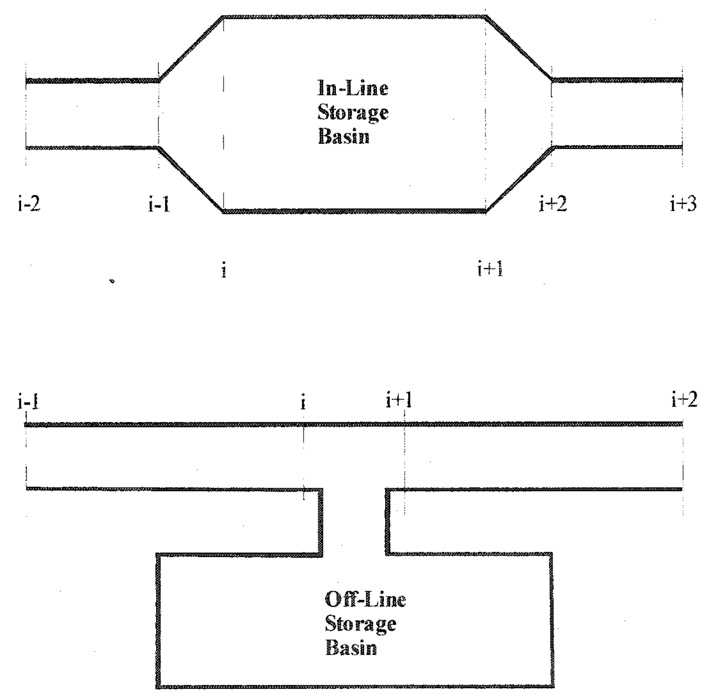

Figure III.8 Conceptual representation of In-line and Of-line storage basin.