**Sedighkia, Mahdi (2022)** ***Optimal operation of dams/reservoirs emphasizing potential environmental and climate change impacts.*** **PhD Thesis, James Cook University.**

# *Optimal operation of dams/reservoirs emphasizing potential environmental and climate change impacts*

**Thesis submitted by**

**Mahdi Sedighkia**

**(2022)**

**For the degree of Doctor of Philosophy (PhD) in the College of Science and Engineering, James Cook University**

## Dedication

***With the memory of my father "Jafar Sedighkia" (1950 – 2018). His inspirations motivated me toward the making of brilliant future. I still feel his hand on my shoulder that encourages me to build a pleasant life for my society and myself.***

**Acknowledgment**

Completing this research work was not possible without almighty God's helps.

I would profoundly like to appreciate my primary advisor Dr. Bithin Datta for his unconditional supports and constructive Comments and critics, throughout the duration of this research work. It is essential to thank my secondary advisor Dr Ahmad Zahedi as well. My appreciations should be dedicated to the Graduate Research School, James Cook University, for providing the financial supports during my study.

Finally, I admire all my family members and friends for helps and supports.

## Statement of the Contribution of Others

The methods and the results reported in this thesis are produced under the supervision of Dr Bithin Datta, who helped me to develop the novel frameworks and reviewed the thesis. All the content of this thesis has been published in the peer-reviewed journals, which means many anonymous reviewers were engaged to produce and improve the research work. Financial assistance for this PhD project was received from RTP scholarship including fortnightly living expenses and tuition fee waiver. Apart from the scholarship by GRS, the College of Science and Engineering provided required computers and electronic tools for handling complex simulations.

## *Important note*

**This research work is originally paper-based thesis in which several published peer-reviewed articles are presented through the chapters 3 to 9. The thesis has an integrated structure in which several independent frameworks through the articles have been developed to improve the dam/reservoir operation with a focus on environmental degradations and potential impacts of climate change. Each framework is useable independently in practice. Some overlaps might be observed in the methods in each chapter. However, we removed repetitive explanations in each chapter based on the proposed style of the PhD thesis by James Cook University. The frameworks have been implemented in several case studies in various weather conditions. Some frameworks have been tested in the same case study. However, the simulated periods (e.g., reservoir inflow etc.) might not be the same.**

## Abstract

This thesis proposes and evaluates several applicable frameworks to optimize diversion dam/reservoir operation considering environmental and climate change impacts. The developed frameworks convert the conventional operation model to the environmental operation model, which is currently a serious need due to increasing population and global warming. Chapter 1 outlines the significance and objectives of the thesis, which is helpful for the readers to identify the purposes and the contributions. Chapter 2 reviews the fundamental concepts and literature consistent with the methods, tools, and models described in the next chapters. Using reliable models to forecast inflow of a dam/reservoir is required for developing a perfect operation model. Hence, chapter 3 presents improvements in the inflow-forecasting model using an adaptive neuro fuzzy inference system (ANFIS) based model for simulating long-term inflow. A wide range of hybrid machine-learning models was tested in which evolutionary algorithms were applied in the training process. Based on the outputs described in this chapter, linked evolutionary algorithm-ANFIS based model is shown to improve the accuracy of simulating long-term inflow of dams compared to those obtained in the few previous recent studies. Chapters 4 to 6 highlight diversion dam operation emphasizing environmental challenges and climate change impacts. Chapter 4 links fuzzy habitat simulation and genetic algorithm (single-objective algorithm) to optimize downstream environmental flow regime. The objective function minimizes the difference between habitat losses and project losses with a focus on water supply. Fuzzy habitat simulation was used to develop the habitat loss function. Based on the outputs of this chapter, minimum available environmental flow in dry seasons was approximately 15% of mean annual flow and reliability index of water supply was 80%. Chapter 5 links machine-learning habitat simulation and irrigation loss function to optimize downstream environmental flow regime of a diversion dam (multi-objective algorithm). Results of this chapter indicated that machine-learning habitat simulation is robust to assess habitat suitability. Moreover, the proposed multi-objective optimization model is able to optimize the environmental flow regime properly. In the case study, the physical habitat impact was minimized to 30%, which means 70% of useable habitats would be protected. In contrast, 60% of water demand would be supplied which implies a fair balance between water supply and environmental flows. Chapter 6 proposes a framework to mitigate the impact of climate change on the optimal operation of a water diversion project. The optimization model maximizes agricultural yield while the impacts of energy use and ecological impacts on the river ecosystem are mitigated. A coupled general circulation model- Soil and Water Assessment Tool (SWAT) was applied to project the impacts of climate change on the stream flow. Results shows that the optimization model reduces the impacts of climate change on agricultural yield by balancing water and energy use. In the pessimistic scenario, water use should be reduced 25% for protecting the river ecosystem. However, the optimization model increases energy use 16% for

preserving the yield. Conversely, the prescribed strategy of the optimistic scenario decreases the energy use 40% compared with the current condition due to increasing water supply. Moreover, physical habitat loss is less than 50%, which means the optimization model protects river habitats acceptably. This novel framework is useable for a reservoir operation model considering some minor changes. Chapters 7 to 9 develop applicable frameworks for environmental operation of reservoirs. Chapter 7 proposes a multipurpose operation model considering downstream water quality impacts. Soil and water assessment tool (SWAT) was applied to simulate downstream river flow and nitrate load. Results shows that the reliability index of water supply is 60%. Furthermore, the failure index of contamination is 0.027. Hence, results corroborate that the proposed optimization system is reliable to mitigate water supply losses and nitrate contamination simultaneously. However, its performance is not perfect for mitigating the impacts of nitrate load in all the simulated months. Chapter 8 develops several useful frameworks of reservoir operation in which the environmental flow model emphasizing water quantity is integrated with the optimization model of a reservoir. Due to the extensive nature of this chapter, more details on these frameworks are available in the contents. Finally, chapter 9 links downstream water quality and quantity requirements of an optimal reservoir operation in which an ecohydraulic-based expert system and evolutionary optimization of reservoir operation are integrated. Three fuzzy inference systems including physical habitat assessment, water quality assessment and combined suitability assessment were developed based on the expert panel method. Moreover, water temperature and dissolved oxygen were simulated by the coupled particle swarm optimization (PSO)–adaptive neuro-fuzzy inference system. Results indicate that the proposed method provides a robust framework for simultaneous management of environmental flow and water supply. The optimization system balances habitat losses, storage losses and water supply losses to deescalate negotiations between stakeholders and environmental managers. This research work demonstrates efficiency of evolutionary optimization for a wide range of water resources management problems. Moreover, a fuzzy technique in order of preference by similarity to ideal solution (FTOPSIS) was used to select the best evolutionary algorithm in several chapters. It is recommendable to apply FTOPSIS as a robust decision-making system in management of reservoirs. The proposed frameworks were tested in several case studies in different climate conditions for showing the capabilities of the simulation-optimization solutions.

## List of publications

Only the list of publications strongly related to the topic and applied in the text of thesis will be mentioned in this section. More publications in the peer reviewed journals during PhD candidature by the author is available in the online platforms

Peer-reviewed journal articles

Sedighkia, M., Datta, B. and Abdoli, A., 2021. Minimizing physical habitat impacts at downstream of diversion dams by a multiobjective optimization of environmental flow regime. *Environmental Modelling & Software*, *140*, p.105029.

Sedighkia, M. and Datta, B., 2022. A simulation-optimization system for evaluating flood management and environmental flow supply by reservoirs. *Natural Hazards, 111*(3), pp.2855-2879.

Sedighkia, M. and Abdoli, A., 2022. Design of optimal environmental flow regime at downstream of multireservoir systems by a coupled SWAT-reservoir operation optimization method. *Environment, Development and Sustainability.* pp.1-21.

Sedighkia, M., Datta, B. and Abdoli, A., 2021. Design of optimal environmental flow regime at downstream of reservoirs using wetted perimeter-optimization method. *Journal of Hydro-environment Research*, *39*, pp.1-14.

Sedighkia, M., Datta, B., Abdoli, A. and Moradian, Z., 2021. An ecohydraulic-based expert system for optimal management of environmental flow at the downstream of reservoirs. *Journal of Hydroinformatics*, *23*(6), pp.1343-1367.

Sedighkia, M., Datta, B. and Abdoli, A., 2021. Optimizing reservoir operation to avoid downstream physical habitat loss using coupled ANFIS-evolutionary model. *Earth Science Informatics*, pp.1-18.

Sedighkia, M., Abdoli, A. and Datta, B., 2021. Optimizing monthly ecological flow regime by a coupled fuzzy physical habitat simulation–genetic algorithm method. *Environment Systems and Decisions*, pp.1-12.

Sedighkia, M., Datta, B. and Abdoli, A., 2022. Reducing impacts of rice fields nitrate contamination on the river ecosystem by a coupled SWAT reservoir operation optimization model. *Arabian Journal of Geosciences, 15(2), pp.1-20.*

Sedighkia, M. and Abdoli, A., 2022. Balancing environmental impacts and economic benefits of agriculture under the climate change through an integrated optimization system. *International Journal of Energy and Environmental Engineering, pp.1-14.*

Sedighkia, M., Datta, B. and Fathi, Z., 2022. Linking ecohydraulic simulation and optimization system for mitigating economic and environmental losses of reservoirs. *AQUA—Water Infrastructure, Ecosystems and Society*, *71*(2), pp.229-247.

Sedighkia, M. and Datta, B., 2021, October. Using evolutionary algorithms for continuous simulation of long-term reservoir inflows. In *Proceedings of the Institution of Civil Engineers-Water Management* (pp. 1-11). Thomas Telford Ltd.

Sedighkia, M., Datta, B. and Abdoli, A., 2022. Reducing the conflict of interest in the optimal operation of reservoirs by linking mesohabitat hydraulic modeling and metaheuristic optimization. *Water Supply*, *22*(2), pp.2269-2286.

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# Chapter 1: General Introduction

## 1.1 Motivation

Diversion dams and large dams play a significant role in water supply around the world. According to the reports of international committee of large dams (ICOLD), more than 560 dams have been constructed in Australia. One of the challenging tasks for all water resource engineers is optimal operation of these hydraulic structures to maximize potential benefits. Most large dams are multipurpose which means they are responsible for water supply, electricity supply and flood mitigation. In contrast, diversion dams are generally applicable for satisfying water demand in urban and non-urban areas. Optimal operation of diversion dams/reservoirs is a complex problem, which needs numerous simulations to provide the optimal release and storage. Environmental degradations of river ecosystems and climate change are important aspects in the environmental management of these hydraulic structures. One of the important research gaps which might be a challenging problem for managing these structures is lack of environmental simulation as well as climate change models in the structure of available dam/reservoir operation models. In other words, available operation models are not able to integrate environmental degradations especially at downstream in the management of a dam/reservoir. It is needed to consider downstream environmental degradations as well as impacts of climate change for optimizing downstream release. In other words, it is required to modify these operation models by adding environmental models and climate change models to the optimization system. This research gap is the main motivation for the present study. Hence, environmental management of hydraulic structures considering environmental degradations and climate change impacts should be highlighted. Based on described research gap, environmental degradations of a diversion dam or a reservoir should be integrated with the optimization model using advanced environmental models, which are able to simulate complex environmental degradations in a river ecosystem. Moreover, design of novel frameworks to optimize reservoir/diversion dam operation is necessary, which should be able to integrate all defined purposes and environmental requirements in one model.

This thesis proposes several simulation-optimization models to improve the conventional operation to environmental operation. In other words, the thesis contributes to propose and evaluate several integrated frameworks to elaborate concept and application of environmental operation in management of a reservoir/diversion dam. Moreover, the impact of climate change on stream flow is highlighted. More details on frameworks including necessities, importance and methodology will be presented in each chapter independently.

## 1.2 Significance

This thesis proposes several ecological-based frameworks for optimal dam/reservoir operation which are able to include downstream environmental degradations as a key component for improving environmental management of dams/reservoirs. Furthermore, impacts of climate change on inflow is added to the framework as well. The following main issues of significance as listed are addressed in this thesis:

1-Environmental impacts of dams have limitedly been addressed in the structure of the dam/reservoir operation which need advanced models to integrate the environmental impacts with the water resources planning

2-Simulation-optimization approaches are essential in the hydro-environmental modelling of dam/reservoir operation in which a wide range of models and tools should be used for environmental problems such as satisfying environmental flow. Moreover, the optimization models should be able to balance the environmental requirements and humans' needs

3-Due to importance of flood mitigation by reservoirs, the robust flood models such as 2D hydraulic models combined with the environmental flow models should be integrated with a reservoir operation model. This integrated model is beneficial for tropical regions in Australia. More details will be presented in next chapters.

4-Advanced water quality models in a river basin scale should be added to a dam/reservoir operation model to maximize environmental benefits of these hydraulic structures.

5- Climate change impacts on stream flow combined with the environmental impacts have rarely been addressed in dam/reservoir management which means impacts and complexities should be discussed.

6- Many methods have been used for forecasting stream flow as a requirement of dam/reservoir management. However, use of new hybrid machine learning methods should be investigated to improve dam/reservoir management.

## 1.3 Objectives

Objectives of this thesis are listed as follows:

1-Development of advanced simulation-optimization frameworks to improve reservoir operation, which convert conventional operation to environmental operation.

2- Optimizing the downstream environmental flows of a dam/reservoir using advanced ecological models of environmental flow.

3- Evaluating different optimization methods including single objective and multi objective algorithms as well as expert systems and hydrological/ hydrodynamic models in the environmental dam/reservoir operation.

4- Incorporating potential climate change impacts in an operation model considering advanced downstream environmental impacts.

5- Defining downstream ecological considerations of water quantity as well as water quality in the structure of operation model.

6- Minimizing environmental impacts on downstream aquatic habitats of dams/reservoir through an ecological operation.

## 1.4 Structure of the thesis

Figure 1-1 shows the structure of this thesis in which the brief content of each chapter and connection between them based on the defined objectives are displayed. The next chapter presents the background of the thesis and a brief literature review on the required tools and models for dam/reservoir operation.

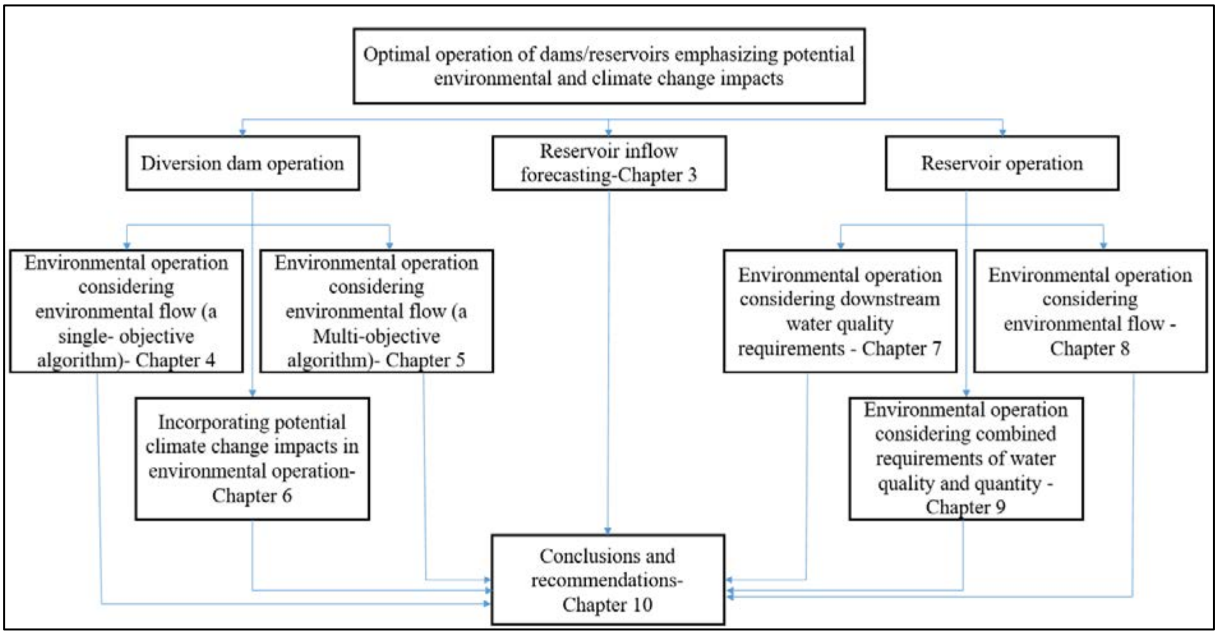


**Figure 1-1- Structure of the thesis**

# Chapter 2: Background and literature review

This chapter reviews background, fundamental concepts, and general literature consistent with the requirements and used modelling frameworks in this thesis. It should be noted that specific literature review would be presented in the introduction of the next chapters for better understating on the developed simulation-optimization frameworks. In other words, each chapter will present an independent framework which could be applied in dam/reservoir management independently.

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## 2.1 Concept of optimal operation of dam/reservoir

The core of this thesis is optimization of reservoir operation. Hence, it is needed to review the key concepts in this regard. In other words, origin of the study is development and evaluation of integrated environmental frameworks to optimize reservoir operation under the current condition and climate change impact. These integrated frameworks assess losses and environmental degradations. Due to importance of optimization methods in dam/reservoir management, this part reviews optimization methods in reservoir operation.

In recent decades, developing optimization techniques of planning and management of complex water resources systems is an important task for engineers. As a general classification of optimization methods, Four main methods including linear programming (LP), non-linear programming (NLP), dynamic programming (DP) and evolutionary algorithms have been proposed in reservoir operation (Ahmad et.al, 2014).

Decision variables used in previous studies were mainly storage and release to maximize the benefits such as water supply. Some studies have been carried out to provide solutions for reservoir operation in small and large dams. Each study considered some effective outcomes in the optimization process. In other words, definition of objective function is a key point for developing optimal strategy in dam/reservoir management. Initially reported studies on reservoir operation considered a simple definition of the specified objective function. However, it became more complex with advances in water resource management. Moreover, uncertainties in reservoir operation especially in some factors such as inflow were another challenge in the optimization process. Witchal and Bhaskar 1978 worked on the optimal operation of Hoover reservoir. They classified tools to develop strategies for reservoir operation as displayed in Figure 2-1

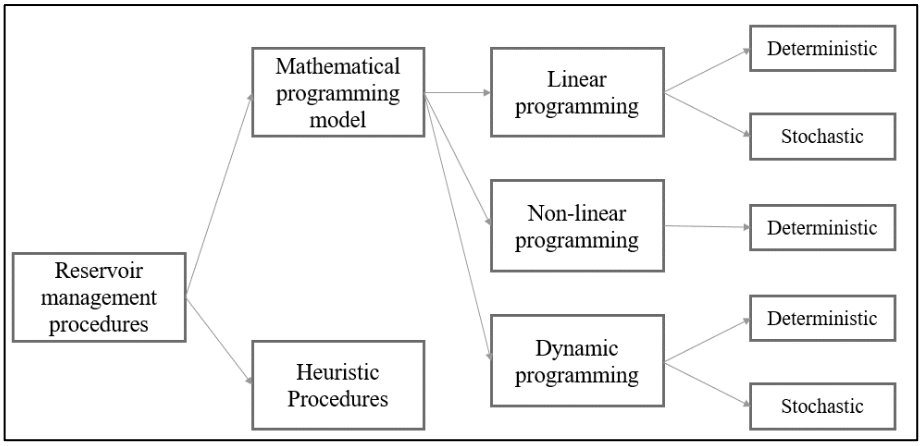


**Figure 2-1- Proposed classification for main optimization procedurs(Witchal and Bhaskar 1978)**

Hashimito et.al, 1982 presented a basic definition on loss function displayed in Equation 2-1

$$l(R) = 0,\ when\ R \geq T;$$
$$l(R) = \left[\frac{T-R}{T}\right]^{\beta},\ when\ R < T \qquad (2\text{-}1)$$

where T is target and R is release to downstream and β is a constant exponent for function which is significantly effective on output. This function highlights the minimum difference between target and release as the point with minimum loss. Datta and Burges (1984) clarified the details of loss function and presented an alternative view on the loss functions for reservoir operation which improved the application of loss function in reservoir operation optimization. Table 2-1 shows brief description on significant old studies in optimal reservoir operation.

**Table 2-1- Significant earlier studies utilizing mathematical models in reservoir operation optimization**

| Subject | Proposed method | Significant results | reference |
|---|---|---|---|
| **Optimizing Energy Generation at the Shiroro Dam Nigeria** | Probabilistic dynamic programming( variable was storage volume) | System was reliable at 45% of power plant factor | Sule 1988 |
| **Application of markov decision processes in real** | Reservoir inflow was described as periodic markov process | Significant computational efficiency results from proposed framework | Wang and Adams, 1986 |

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| **time reservoir optimization** | | | |
| **New linear programming approach for optimization** | Proposing an integrated linear programming method for a typical combined system in a river | Discussion on advantages of proposed method in case study | Jacovkis et.al 1989 |
| **Sampling stochastic dynamic programming applied to reservoir operation** | Considering temporal and spatial structure of inflow by using a large number of sample streamflow sequence monthly | Case study in California described performance of SSDP approach | Kelman et.al, 1990 |
| **Iterative method to optimize reservoir systems** | Combination of dynamic programming with successive approximation and state incremental dynamic programming | Proposed method is applicable for complex configuration due to low convergence by other iterative methods | Bayazit and Ildiz, 1987 |
| **Bayesian stochastic optimization of reservoir operation** | Combined stochastic dynamic programming and Bayesian decision theory (Inflow, storage and forecast as state variables) | Discussion on differences of proposed method and previous stochastic dynamic programming methods | Karamouz and Vasiliadis, 1990 |
| **Multi-stage flood routing for gated reservoirs and conjunctive of hydro-electricity income with flood losses** | Dynamic programming to optimize both the firm and secondary energies of monthly hydroelectric generation | Optimum active and flood retention storage to maximize electricity benefit minus flood damage cost | Acanal et.al, 2000 |
| **Optimization of multi reservoir network for sedimentation control** | Discrete time optimal control by linear quadratic regulator optimization scheme | Users can evaluate policies could maximize sedimentation and computational efficiency of proposed method and differential dynamic programming method | Nicklow et.al, 2000 |
| **Use of stochastic dynamic programming to optimize water allocation in Nebhana reservoir** | Application of SDP method to optimize operation by considering two opposite objectives which were supply of irrigation water demand | Identification of optimize rules to estimate water release volume | Alaya et.al,2003 |

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| | and guarantee of minimal storage | | |
| **Stochastic optimization to derive operating rules of reservoir** | Generating synthetic inflow scenarios and using optimization model to find optimal releases | Results were highly correlated with optimization models under perfect forecast | Celeste et.al, 2005 |
| **Optimization profit from hydroelectricity production** | Application of deterministic and stochastic mathematical model to maximize profit by selling electricity | Superiority of stochastic model | Ladurantaye et.al, 2007 |
| **Optimization of Korean multi reservoir system** | Application of sampling stochastic dynamic programming with ensemble stream flow prediction | Proposed stochastic models that include explicitly inflow uncertainty are superior | Kim et.al, 2005 |

Using evolutionary algorithms is an efficient solution to solve optimization problems (Bozorg-Haddad et.al, 2016). Many methods have been developed by evolution of complex methods which is generally called computational intelligence methods. Evolutionary algorithms such as Genetic Algorithm, Simulated Annealing, Tabu Search, Particle Swarm Optimization, Honey Bees Mating Optimization and several other algorithms could be applicable for solving nonlinear and multi-objective problem of reservoir optimization. Different studies applied evolutionary algorithm as an optimization method to solve nonlinear problem of reservoir optimization. For example, the genetic algorithm(GA) imitates the process of natural evolution (Whitley, 1994; Chang et.al, 2005). it has been used in several studies to optimize the operation(eg. Wardlaw and Sharif, 1999). Moreover, hybrid algorithms have been applied in reservoir operation as well (Cheng et.al, 2008; Tospornsampan et.al, 2005). Table 2-2 reviews some important studies by evolutionary algorithms in the water resources optimization.

**Table 2-2- A list of studies with a focus on using evolutionary algorithms**

| Used algorithm | Algorithm's origin | Reference(s) in reservoir optimization |
|---|---|---|
| **Genetic algorihtm (GA)** | evolutionary inspired by the process of natural selection, Developed by John Holland, 1960 based on the concept of Darwin's theory of evolution | Wardlaw and Sharif, 1999 |

| | | |
|---|---|---|
| **particle swarm optimization (PSO)** | Moving population of candidate solutions as particles in the search-space developed by Eberhart and Kennedy, 1995 | Kumar et.al, 2007 |
| **Ant colony optimization (ACO)** | Inspired by the behavior of real ants, Initially developed by Marco Dorigo, 1992 | Kumar, et.al, 2006 |
| **Harmony search algorithm (HSA)** | inspired by musical performance process, developed by Geem et.al, 2001 | Bashiri-Atrabi et.al, 2015 |
| **Gravity search algorithm (GSA)** | based on the law of gravity and mass interactions, developed by Rashedi et.al, 2009 | Bozorg-Haddad et.al, 2016 |
| **Spider monkey algorithm(SMA)** | Based on modelling the foraging behavior of spider monkeys, developed by Bansal et.al 2014 | Ehteram et.al, 2018a |
| **Bat algorithm (BA)** | inspired by the echolocation behaviour of microbats developed by Xin-She Yang 2010 | Ethteram et.al, 2018c |
| **Firefly algorithm (FA)** | inspired by the flashing behavior of fireflies, developed by Yang, 2008 | Garousi-Nejad et.al, 2015 |
| **Honey bees algorithm (HBA)** | Inspired by food foraging behaviour of honey bee colonies, developed by Ghanbarzadeh , 2007 | Afshar et.al, 2007 |
| **Hybrid bat-swarm algorithm (HBS)** | It used as hybrid algorithm for reservoir optimization by Yaseen et.al, 2019 | Yaseen et.al, 2019 |
| **Kidney algorithm (KA)** | Inspired by kidney performance in four steps: filtration, reabsorption, secretion, and excretion, developed by Jaddi et.al, 2017 | Ehteram et.al, 2018b |
| **Water cycle algorithm (WCA)** | Inspired by flow movement from streams and rivers to sea in real world, developed by Eskandar et.al, 2012 | Haddad et.al, 2015 |
| **Biogeography based optimization algorithm (BBO)** | Inspired by distribution of biological species through time and space, Developed by Dan Simon, 2008 | Haddad et.al, 2016 |
| **Simulated annealing algorithm (SAA)** | Inspired by annealing in metallurgy (Fleischer,1995) | Teegavarapu and Simonovic, 2002 |
| **Differential evolution algorithm (DE)** | It iteratively tries to improve an agent with regard to a given measure of quality (refer to Reddy and Kumar, 2007) | Reddy and Kumar, 2007 |
| **Teaching learning based optimization algorithm (TLBO)** | Inspired by teaching–learning phenomenon of a classroom, developed by Rao and Kalyankar, 2011 | Kumar and Yadav, 2018 |
| **Cat swarm optimization algorithm (CSO)** | Inspired by behavior of cat includes tracing and seeking modes and motivated from PSO and ACO, Developed by Chu et.al, 2006 | Bahrami et.al, 2018 |

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|---|---|---|
| **penguins search optimization algorithm (PeSOA)** | based on collaborative hunting strategy of penguins, developed by Gheraibia and Moussaoui, 2013 | Mansouri et.al, 2018 |

## 2.2 Simulation methods in dam/reservoir management

It is required to apply different types of simulations in the structure of the optimization model for an effective water resources management. In this section, all the potential simulations needed in the optimal operation of dam/reservoirs will be reviewed briefly.

### 2.2.1 Rainfall-runoff modelling (water quantity and water quality modelling)

Simulating reservoir inflow is a primary need in many cases. Prediction of outflow in a catchment has been a key question for engineers for many years. Design, planning, assessment, and maintenance of hydraulic structures need an accurate prediction of inflow. Initial structure of runoff routing models is displayed in Figure 2-2.

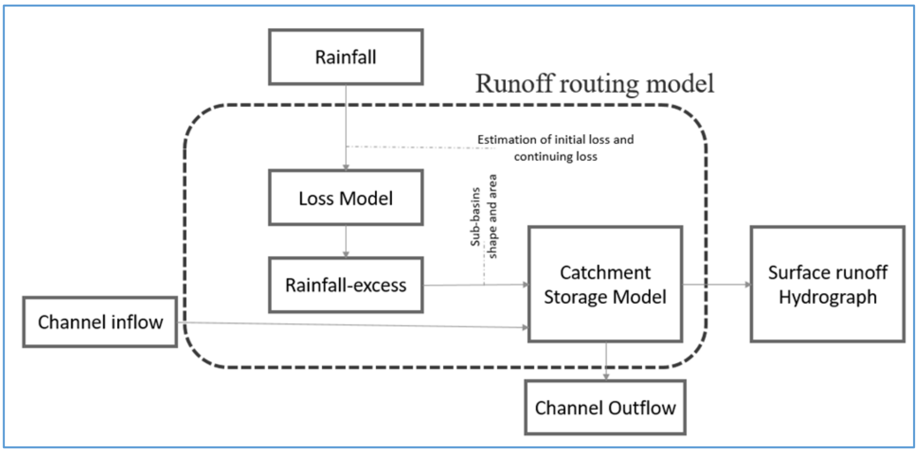



**Figure 2-2- Runoff routing model framework (Laurenson et.al, 2017)**

A loss model is considered as a main component of runoff routing, which eliminates permeated rainfall to the ground. Therefore, channel outflow and surface runoff hydrograph would be obtained by routing excess rainfall in a catchment. Routing models of the channel, stream and floodplain reaches are the key components in hydrologic assessment in all catchments. Australian rainfall and run off 2016 has been reviewed routing models which is one of the reliable scientific references for rainfall-runoff modelling (Ball et.al, 2016). For example, RORB as one of the popular and known Australian models carries out routing process based on concentrated non-linear storage. More details on event-based models have been addressed in the literature (Srinivasan and Galvao, 1991; Laurenson et.al, 2010; Knapp et.al, 1991; Rogger et.al 2012; Svensson et.al 2013; Nandakumar and Mein, 1997;Kemp, 2017).

Continuous simulation is recommended to cover disadvantages of event-based models. Soil and Water Assessment Tool (SWAT) uses spatially distributed data on topography, soils, land cover, land management, and weather to predict runoff, sediment, nutrient, pesticide, and fecal bacteria yields by a continuous simulation approach (Sinnathamby et.al, 2017). Moreover, SWAT-CUP has been developed as a stand-alone software to calibrate and validate SWAT's output (Abbaspour, 2013).

Data-driven models could be applied in rainfall-runoff modelling as well (Lobbrecht, et.al, 2002). Neural networks have been extensively used in runoff routing (e.g. Anmala et.al, 2000; Machado et.al, 2011). Tayfur and Singh, 2006 developed ANN and fuzzy logic model to predict event-based rainfall runoff and compared results with the kinematic wave approximation. Moreover, adaptive neuro fuzzy inference system has been successfully applied to forecast reservoir inflow (Awan and Bae, 2014).

### 2.2.2 Flood modelling

Most large dams are multipurpose which means flood mitigation might be an objective in reservoir operation. Hence, flood modelling is needed in some reservoir operation models. One-dimensional hydraulic modelling was the first effort to develop numerical river hydraulic models. HEC-RAS is one of the earlier and known models used for simulating floods. Different versions of this model have been released in recent decades (Brunner, 2002; Horritt and Bates, 2002;Teng et.al, 2017). HEC-RAS is able to compute one dimensional water surface profile for steady gradually varied flow Subcritical, supercritical, and mixed flow regime in natural or channelized streams. It can mathematically solve unsteady flow hydrodynamics by solving partial differential equations governing river flow. Advances in open channel hydraulic studies indicated that river flow in floodplains is two-dimensional. Hence, Using 2D hydraulic modelling for advanced simulation of floods is essential (Teng et.al, 2017). Table 2-3 provides an applicable review on robust, popular and known 1D and 2D or combined 1D/2D models which could be applied in flood modelling at downstream of reservoirs.

**Table 2-3- Summary Review of widely used commercial hydraulic models to simulate depth, velocity and extent of river flow**

| Name | Reference(s) | Numerical Method | GUI | Abilities |
|---|---|---|---|---|
| **HEC-RAS 4.0-1D** | Us-Army Corps-(Brunner, 2010) | Solving one dimensional energy equation. Energy losses are evaluated by friction (Manning's equation) | Developed independent GUI | Suitable for one-dimensional hydraulic modelling in river main channels. It is not enough accurate for hydraulic modelling in flood plains |

| | | | | |
|---|---|---|---|---|
| | | and contraction/expansion. The momentum equation is used in rapid varied surface profile | | |
| **HEC-RAS 5.0-2D** | Us-Army Corps-(Brunner, 2016) | Numerical scheme: Finite volume, Discretisation of time: Implicit, Discretisation of space: Originally unstructured mesh but is able to handle structured mesh | Developed independent GUI | Is able for 1D,2D and 1D/2D combined hydraulic modelling. Suitable for large flood plain systems connected to main channel of river |
| **MIKE 11** | MIKE 11 user guide | Solving one dimensional energy equation. Energy losses are evaluated by friction (Manning's equation) and contraction/expansion. The momentum equation is used in rapid varied surface profile | Developed independent GUI | Suitable for one-dimensional hydraulic modelling in river main channels. It is not enough accurate for hydraulic modelling in flood plains. It is part of MIKE DHI package to simulate 1D,2D and 1D/2D combined modelling with other module such as MIKE FLOOD. MIKE DHI package is one of the known European packages for integrated hydraulic modelling |
| **MIKE 21** | MIKE 21 user guide | Numerical scheme: Finite Volume, Discretisation of time: Explicit, Discretisation of space: Structured mesh | Developed independent GUI | It is able to simulate hydraulic and environmental phenomena in lakes, estuaries, bays, coastal areas and seas by structured mesh. It is part of MIKE DHI package to simulate 1D,2D and 1D/2D combined modelling with other module such as MIKE FLOOD. MIKE DHI package is one of the known European packages for integrated hydraulic modelling |
| **MIKE 21 FM** | MIKE 21 FM user guide | Numerical scheme: Finite Volume, Discretisation of time: Explicit, Discretisation of space: flexible mesh | Developed independent GUI | It is able to simulate hydraulic and environmental phenomena in lakes, estuaries, bays, coastal areas and seas by flexible mesh. It is part of MIKE DHI package to simulate 1D,2D and 1D/2D combined modelling with other module such as MIKE FLOOD. MIKE DHI package is one of the known European packages for integrated hydraulic modelling |
| **TUFLOW Classic** | TUFLOW Classic/HPC User Manual | Numerical scheme: Finite difference, Discretisation of time: Implicit, Discretisation of space: Structured mesh | Third Party GUI | TUFLOW's fixed grid solver is a world leading 1D/2D and 2D/2D dynamic linking numerical engine. Suitable for integrated urban drainage situations (above and below ground), distributed hydrology direct rainfall scenarios, catchment flooding, tides and storm tide hydraulics. |
| **TUFLOW FV** | TUFLOW FV User Manual | Numerical scheme: Finite volume, Discretisation of time: Explicit, Discretisation of space: Flexible mesh | Third Party GUI | One-dimensional (1D), two-dimensional (2D) and three-dimensional (3D) Non-Linear Shallow Water Equations (NLSWE), suitable for wide range of hydrodynamic systems ranging in scale from the open channels and |

| | | | | |
|---|---|---|---|---|
| | | | | floodplains, through estuaries to coasts and oceans |
| **XP2D** | XP2D User manual | Numerical scheme: Finite difference, Discretisation of time: Implicit, Discretisation of space: Structured mesh | Third Party GUI | Suitable for two and one-dimensional free-surface flows due to floods and tides which is based on computational engine TUFLOW and dynamically linked (fully integrated) with the xpswmm and xpstorm 1D solution engine |
| **CCHE1D** | CCHE1D user manual | Solving one dimensional energy equation. Energy losses are evaluated by friction (Manning's equation) and contraction/expansion. The momentum equation is used in rapid varied surface profile | Developed independent GUI | Suitable for one-dimensional hydraulic modelling in river main channels. It is not enough accurate for hydraulic modelling in flood plains |
| **CCHE2D** | CCHE2D user manual | Numerical scheme: Finite difference, Discretisation of time: Implicit, Discretisation of space: Structured mesh | Developed independent GUI | It is included a mesh generator which generates structured mesh and a graphical user interface which simulates generated domain by a two dimensional hydraulic modeller |

### 2.2.3 Impact assessment of climate change

Causes and global impacts of climate change have been an attractive subject for meteorological scientists. However, environmental and water resources engineers focus on assessment of impacts of global warming on hydrologic systems such as river basins. General Circulation Models (GCMs) are popular tools for simulating hydrological system response such as river basin by depiction of the climate in three dimensional grid over the globe. These models commonly have coarse horizontal resolution (250 to 600 km). They consider 10 to 20 vertical layers in the atmosphere (Wilby and Wigley, 1997; Wilby et.al, 2002). However, simulating impacts needs smaller scale, which means direct use of GCMs in hydrological systems increases uncertainties. Downscaling presumably reduces uncertainties of GCMs for applying in a river basin scale. Two types of methods are available for downscaling including statistical downscaling methods and dynamic downscaling methods. Due to lower cost by statistical downscaling methods, they are popular in practical studies. Statistical downscaling model (SDSM) software and Long Ashton research station weather generator (LARS-WG) are known and popular tools for simulating climate change impacts in hydrology (Hashmi et al. 2011; Hassan et al. 2014). The previous studies demonstrated potential impacts of climate change in water resources planning which means using mathematical models of climate change impacts is necessary (Chiew et.al, 1995; Chen et.al, 2012). For example, Rzaee Zaman et.al, 2013 reported that stream flow will be decreased 21% by the year 2099. However, Lubini & Adamowski, 2013 claimed that river flow would be increased 24% to 45% by the year 2099. Hence, simulating potential impact of climate change is needed case by case.

## 2.3 Summary

The present chapter briefly reviewed basic methods and models in optimal management of dams/reservoirs considering environmental and climate change impacts. We need a wide range of mathematical tools and models for an effective operation of a diversion dam or a reservoir. This thesis uses several mathematical tools in development of novel frameworks of dam/reservoir operation. Specific literature review on the developed method and used tools and models will be presented in each chapter independently. Each chapter proposes an independent framework. Hence, each framework is discussed independently as applications need detailed description. Some overlaps in the literature review and methodology might be observed.

## Chapter 3: Reservoir inflow forecasting

Full contents of this chapter have been published and copyrighted, as outlined below:

Sedighkia, M. and Datta, B., 2021, October. Using evolutionary algorithms for continuous simulation of long-term reservoir inflows. In Proceedings of the Institution of Civil Engineers-Water Management (pp. 1-11). Thomas Telford Ltd.

### 3.1 Introduction

The roles of dams in the development and supply of drinking water and satisfying irrigation, industrial water demands and hydropower generation have been widely discussed (Keller et al., 2000). Optimising reservoir operation (one of the main tasks in reservoir management) has been a research focus in recent decades (Ahmad et al., 2014; Bahrami et al., 2018; He et al., 2019; Rabiei et al., 2018; Samadi-koucheksaraee et al., 2019). Long-term inflow forecasting is critical to regulate the operation of reservoirs for flow control, but one of the challenges for the optimisation of reservoir operation is accurate prediction of the inflow to reservoirs. The aim of this study was thus to develop and evaluate the performance of coupled evolutionary algorithm–adaptive neural fuzzy inference system (EA–ANFIS) models for simulating long-term monthly inflows to a reservoir.

Data-driven models have been employed in environmental engineering as tools to predict or simulate hydrological parameters such as runoff in a catchment (Lobbrecht et al., 2002). Artificial neural networks (ANNs) have been used to forecast reservoir inflows. Previous studies have demonstrated that ANNs are a valuable tool for reservoir inflow simulation or forecasting, and therefore for optimal reservoir operation (Jain et al., 1999). Inputs such as the preceding inflow, temperature and precipitation have been considered in ANN-based forecasting inflow models (Coulibaly et al., 2000). Feed-forward networks are the most suitable for simulating reservoir inflow, but other types of networks such as the delayed neural network and recurrent neural network have also been used (Coulibaly et al., 2001). Time series models such as autoregressive moving average (Arma) and auto-regressive integrated moving average (Arima) are other suitable methods to simulate reservoir inflows. Based on previous studies, Arima models perform better than Arma models, as the number of input parameters is increased (Valipour et al., 2013). Another set of data-driven models applied to reservoir operation and management are fuzzy sets or models based on fuzzy logic. Fuzzy logic is a powerful tool for the management of reservoir operation (Ahmadianfar et al., 2017; Dubrovin et al., 2002; Panigrahi and Mujumdar, 2000). ANNs and fuzzy inference systems have intrinsic advantages and drawbacks, and neuro fuzzy systems such as the adaptive neuro fuzzy inference system (ANFIS) have been found to enhance the predictive skills of data-driven models. ANFIS is a computational tool based on the Takagi–Sugeno fuzzy inference system that constructs a map of the connections between inputs and output(s) by using fuzzy if–then rules and stipulated data pairs (Jang, 1993). ANFIS has been successfully used to develop reservoir operation rules and predict changes in storage levels (e.g. Soltani et al., 2010; Valizadeh and El-Shafie, 2013). ANFIS-based models for simulating reservoir inflow have been addressed in earlier studies. According to El-Shafie et al. (2007), ANFIS is able to simulate reservoir inflow more accurately than ANNs. The ANFIS method has been used to forecast long-term reservoir inflows using different models (Awan and Bae, 2014). Six models were developed using different combinations of inputs. As a result, if different combinations of inputs include the preceding inflow and rainfall data, the model will properly simulate reservoir inflow.

EAs are robust methods for optimisation and have been extensively used to optimise reservoir release in recent years (e.g. Bozorg-Haddad et al., 2016; Garousi-Nejad et al., 2016). Many previous studies have highlighted the application of EAs for reservoir operation and stream flow prediction (e.g. Adnan et al., 2019; Bozorg-Haddad et al., 2017; Chang and Chang, 2009; Kashid et al., 2010; Ladanu et al., 2020; Özger, 2009; Reddy and Kumar, 2006). However, the performance of EAs can differ depending on the defined optimisation problem and the use of different EAs may thus be necessary to establish the best one to solve an optimisation problem. The connection between inflow predictions, the prediction tool (ANFIS) and the use of an EA to train the prediction tool needs to be clarified. Simulating stream flow or reservoir inflows is a complex task as many factors can affect the generation of runoff in a catchment. Using continuous hydrologic models might be a robust option (Vazquez-Amábile and Engel, 2005), but these models need broad input data at catchment scale (e.g. flow, weather data, land use maps) and some of these data may not be available in many real-life cases. Moreover, the calibration and validation of these models can be difficult. Data-driven models such as ANFIS-based models are possible alternatives in this regard because these models are able to create maps between key effective factors and stream flow. These models only need key effective factors such as preceding flows and rainfall data, which are generally easily available. The training process is the most important step in the development of ANFIS-based models. Conventional training methods such as hybrid algorithms have been used in previous studies (Awan and Bae, 2014), but it seems that the robustness of previous models to simulate inflows needs to be improved. Inflow simulation or prediction models generally utilise optimal solutions, they are also a kind of optimisation problem. Solving complex optimisation problems is an active research area. Improving the results of ANFIS-based model requires more robust optimisation methods such as EAs.

The present chapter contributes to the development of a robust daily ANFIS model to simulate monthly long-term reservoir inflow. This should be helpful for improved long-term management of reservoir operations. The main advantage of the proposed method is the availability of the required data in most catchments. Hence, in practice, only minimum effort is needed by the modeller to provide input data.

The focus of the present chapter was, however, to evaluate performance of a coupled EA–ANFIS model to simulate long-term reservoir inflow. The results showed improvements in monthly long-term reservoir inflow simulation. Regarding the focus of the present chapter, it should be noted that this work was confined to the simulation of inflow and did not extend to the prediction of future inflows with different forecasting lead times. However, testing of the simulation results can be considered as analogous to testing the developed inflow model based on an ideal scenario equivalent to perfectly predicted rainfall (i.e. an ideal scenario). A rainfall forecasting model was not developed in the present chapter. The ANFIS-based model was thus used to simulate reservoir inflow for a testing period in which recorded rainfall was available. In other words, the aim of this study was to develop a robust data-driven model to simulate reservoir inflow. However, the developed model could be coupled with a robust rainfall forecasting model to forecast reservoir inflow in future periods.

## 3.2 Methodology

### 3.2.1 Study area

The Ross River dam and reservoir in northern Queensland, Australia, was considered as a case study. The Ross River is an important river in Queensland. The dam is a rock and earth fill embankment dam located in Townsville city. Figure 3-1 shows the location of Ross River reservoir and the related catchment area that feeds reservoir storage; the main characteristics are\ shown in Table 3-1. The average annual rainfall in the catchment is 1143 mm and rainfall in wet seasons can be considerable. However, there is considerable variation from year to year. The total annual inflow of the reservoir is 1600–1800 million $m^3$. January to April is the most significant flood season in the area, with remarkable floods previously experienced in this period of the year. The two main purposes of the reservoir are flood control (possible by using the gate spillway) and the supply of water to urban areas.

Flood mitigation is the primary purpose of the reservoir as floods in the wet season can cause damage to the urban area downstream of the reservoir. In other words, minimising the inundation of downstream urban areas is the focus of flood mitigation. Urban areas lie very close to the main channel of the Ross River, meaning that reservoir must reduce inundation areas in the flood plain. Based on reports by Townsville city council, if the annual exceedance probability of flooding is less than 5%, flood damage may be considerable. The role of the reservoir in reducing flood damage is thus significant. As already mentioned, water supply to Townsville city is another purpose of the reservoir. The total daily water demand of Townsville is 750 l/day per person; this includes water for drinking, industrial demand and irrigation. Ross River reservoir is only one of the water resource infrastructures for Townsville city; there are also other alternative sources. Specific targets for water supply have thus not been defined, but the Ross River reservoir contributes in a major way to Townsville's water supply. In this study, recorded data of daily inflow and average rainfall in the catchment over the period 2000–2017 were used for training; data for 2017–2019 (36 months) were used for testing to validate the simulation model. Error metrics were obtained for the testing period.

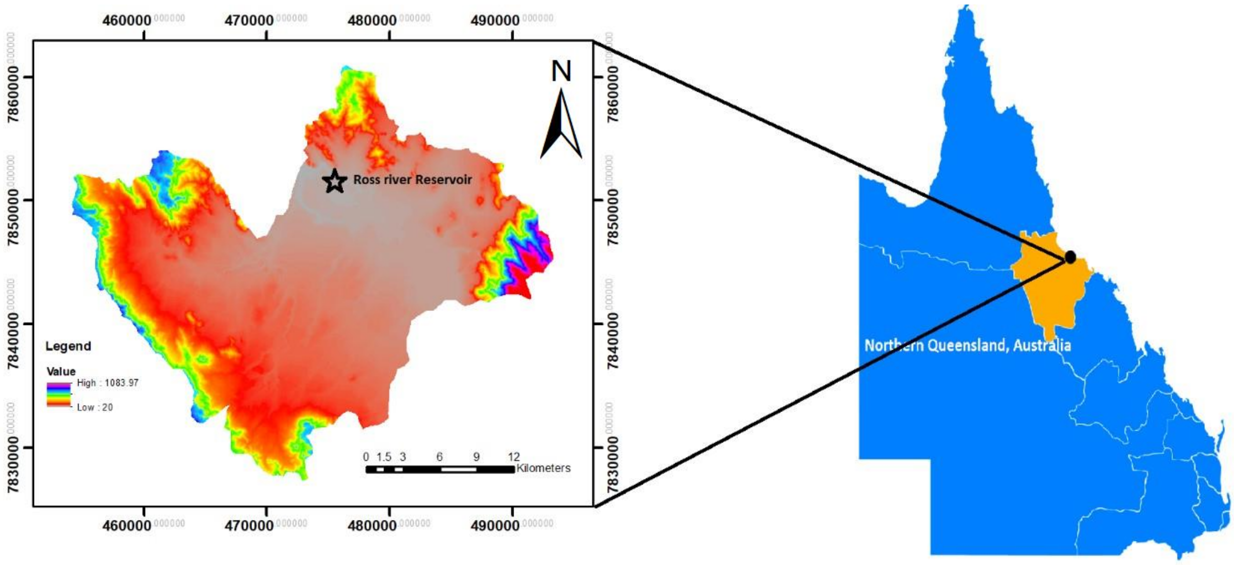



**Figure 3-1- Location of Ross river reservoir and its catchment**

**Table 3-1-Main characteristics of Ross river dam**

| | |
|---|---|
| **Capacity (Mega litres)** | **250000 (Approximate)** |
| **Length of earth rock embankment(Km)** | 8.67 |
| **Height (m)** | 34 |
| **Type of spillway** | Controlled gated spillway |
| **Catchment area (Km$^2$)** | 750 |

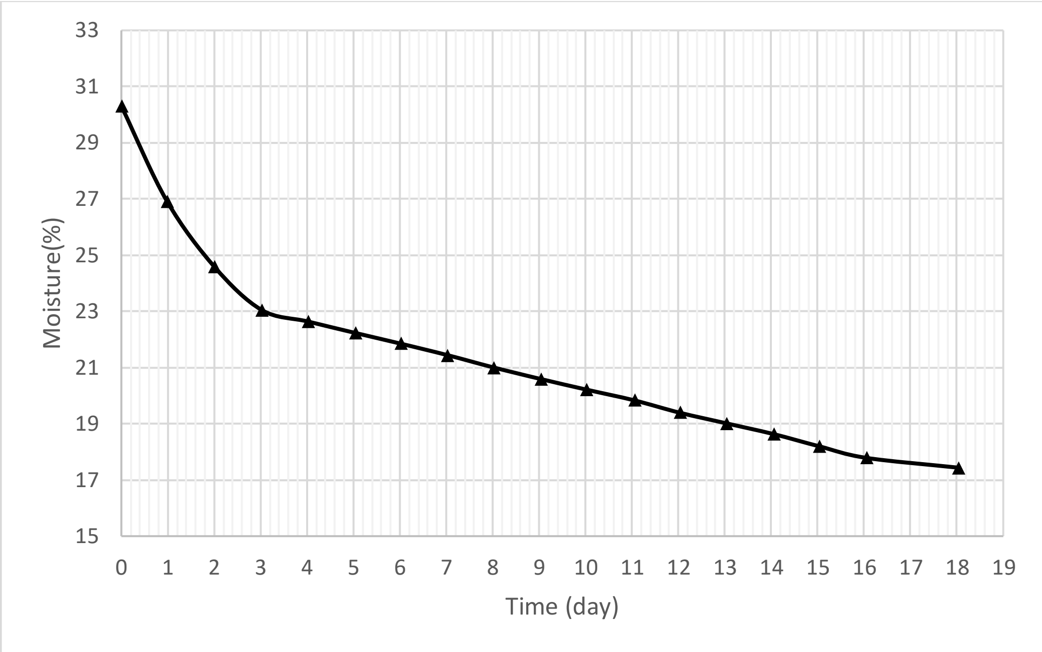



**Figure 3-2-Relationship between soil moisture and number of days after each rainfall event**

### 3.2.2 ANFIS structure

Three main data input patterns were considered in the structure of the ANFIS model – daily rainfall data, preceding inflow and soil moisture. An approximate relationship between time after rainfall and soil moisture content (%) was used to estimate soil moisture. This relationship was able to estimate the average soil moisture content for 0–30 cm of the soil surface. Hence, it was possible to calculate the approximate moisture content for each day based on previous rainfall events. The relationship used to estimate soil moisture is shown in Figure 3-2. It should be noted that providing precise data to calculate the trend of moisture after rainfall can be complex. The use of an approximate relationship between time after rainfall and soil moisture is thus one of the most important aspects of this study. The curve shown in Figure 3-2 is based on limited recorded soil moisture data over the period 2000–2010. Thus, if the developed model is able to simulate inflow accurately using approximate soil moisture estimates, it will be a useful model for practical cases that may not need soil moisture estimation at each time step.

The main structure of the reservoir inflow simulation in the present chapter is based on ANFIS. Some details on the ANFIS architecture may thus be useful. A general view of the architecture of ANFIS is shown in Figure 3-3. In this sample representation, two inputs are considered (X and Y) with a rule base of two of the Takagi–Sugeno type. Generally, the ANFIS architecture has five layers. Layer 1 includes the input membership functions (MFs). Layer 2 includes fixed nodes, which give outputs as a product of all incoming signals. Layer 3 also has fixed nodes, which compute the normalised firing strength of each rule. Layer 4 includes adaptive parameters that are changed during the training process. Finally, a

single node in layer 5 computes the overall output as a summation of all incoming signals. More details on parameters are available in the literature (Awan and Bae, 2014; Azamathulla et al., 2009).
Figure 3-4 shows the workflow of ANFIS in predicting reservoir inflow. In ANFIS training, the premise and consequent parameters can be updated in several ways. Among the conventional methods, the hybrid training approach combines gradient descent and the least squares method, and is efficient. Moreover, a hybrid algorithm was used by Awan and Bae (2014) to simulate monthly reservoir inflow. The back-propagation approach is generally not efficient (Awan and Bae, 2014) and hence was excluded from the present chapter. As shown in Table 3-2, in this study, ten MFs were used for each input pattern. Using a hybrid algorithm for several MFs is not efficient in terms of computation time and computational error is also possible. The use of an EA is robust and efficient at training an ANFIS model when a complex architecture including numerous MFs is considered in the simulation. The main features of the developed ANFIS structure used to simulate inflow are shown in Table 3-2. The most important effective factors were considered as inputs to the model. The proposed model requires the least amount of data, which is an advantage. Recorded rainfall is the main requirement for the model, and such data are available in most catchments. Moreover, the recorded reservoir inflow on the first day of modelling is required to run the data-driven model for a longer period. By averaging daily data to monthly data, long-term monthly inflow data can be simulated (or forecasted if forecasted rainfall is one of the inputs), which is very useful for improving reservoir management. A Gaussian model with ten MFs (very low, low, more or less low, low to medium, medium, more or less medium, high, more or less high, very high and extremely high) was used for the inputs. Using ten MFs could be helpful for increasing the predictive skill of the model. Ten MFs were also used for the output (i.e. simulated inflow at time step t+ 1). However, these MFs were linear.

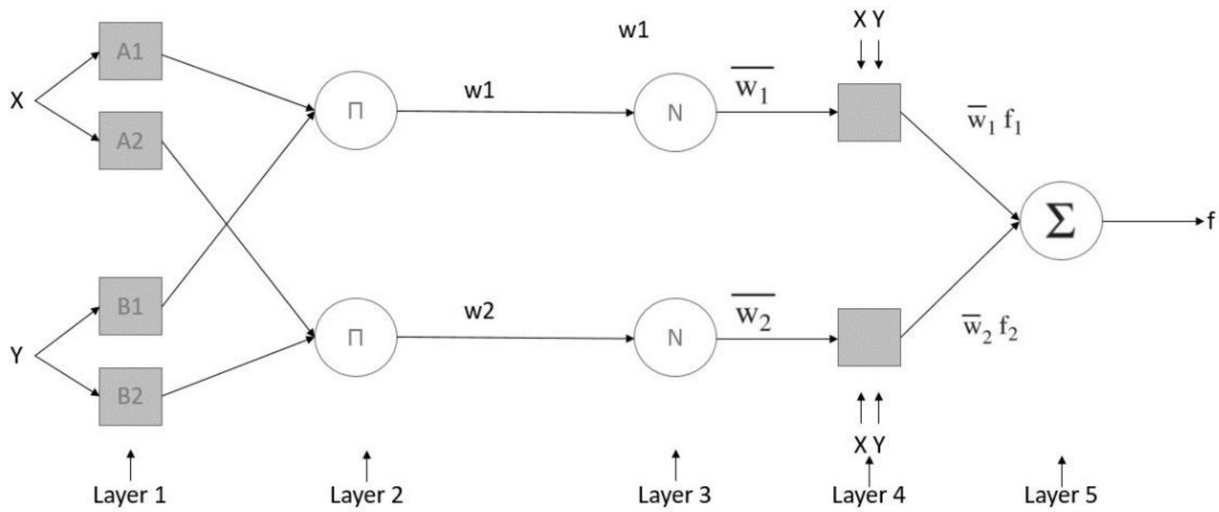



**Figure 3-3- ANFIS architecture**

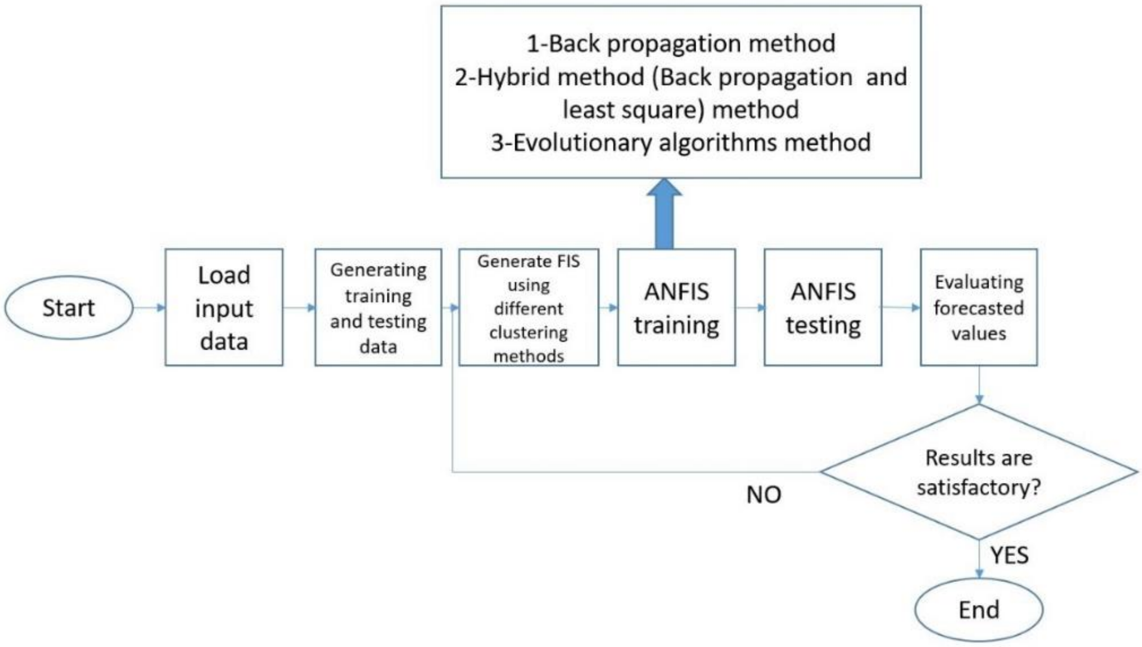



**Figure 3-4- General workflow of ANFIS**

### 3.2.3 Evolutionary algorithms

Figure 3-5 shows a general EA flowchart. EAs can be classified into two main classes – animal- and non-animal-inspired algorithms (Jahandideh-Tehrani et al., 2019). The former generally imitate the social behaviour of animals whereas the latter are inspired by other patterns such as physical laws. A wide range of evolutionary algorithms has been developed, including genetic algorithms (GAs) (Whitley, 1994), particle swarm optimisation (PSO) (Kennedy and Eberhart, 1995), the shuffled frog leaping algorithm (SFLA) (Amiri et al., 2009), biogeography-based optimisation (BBO) (Simon, 2008), harmony search algorithms (HSAs) (Yang, 2009), differential evolution algorithms (DEAs) (Qin et al., 2008), invasive weed optimisation (IWO) (Mehrabian and Lucas, 2006) and cultural algorithms (CAs) (Reynolds, 1994). The methodology of the algorithms and the reasons for their selection are now reviewed.

GAs are well-known and popular algorithms inspired by Darwin's theory of evolution. GAs have been used in many environmental engineering areas, such as water quality models and reservoir management (e.g. Chen, 2003; Park et al., 2006). In the first step of a GA, a random assortment of chromosomes is selected to be used as the first generation (initial population). Each chromosome in the population is then evaluated by a fitness function. If the required condition is not satisfied by the first generation, a selection operator selects some chromosomes for reproduction: the cross-over operator resembles biological crossing over whereas the mutation operator randomly flips individual bits in the new chromosome. Iterations are carried out until the fitness value of the 'best-sofar' chromosome stabilises or the maximum number of iterations is exceeded. PSO is another well-known and relatively old algorithm for optimisation problems. This algorithm simulates the social behaviour and movement of organisms in, for example, a flock of birds or a school of fish. In PSO, the position of particles is randomly selected in the first step and the global best particle position is determined. By computing the velocity of each particle, the positions of particles are updated. The SFLA is a relatively unknown animal-inspired algorithm that imitates behaviour of frogs. In other words, the population includes a set of artificial frogs as possible solutions. The methodology of this algorithm is similar to PSO, but all the frog position vectors are randomly initialised. BBO follows a natural process pattern. It was inspired by the distribution of biological species through time and space and was originally developed by Simon (2008). BBO is based on speciation (the evolution of new species), the migration of species (animals, fish, birds or insects) between islands and the extinction of species. In the first step, random habitats are selected as the initial population and two migration and mutation operators are applied. The habitat suitability value is the main criterion in this algorithm. The HSA mimics the improvisation process of musicians finding a pleasing harmony (Yang, 2009). Harmony memory is considered as the population or search space in this algorithm, and the initial random harmony is compared with an improvised harmony. If the improvised harmony is better than the original harmony, it will replace the original. The process is stopped when the maximum number of iterations is reached.

Previous researchers have recommended using EAs to train ANFIS-based models (e.g. Qasem et al., 2017; Zangeneh et al., 2011), so the algorithms described above were assessed in this work. Similar initial common parameters (e.g. population size) were considered in all the algorithms to ensure fair comparison to the extent feasible. Training ANFIS-based models is a special kind of optimisation problem. Efficient and novel optimisation algorithms such as EAs could thus be used to improve tuning of the parameters and each evolutionary algorithm might be useful in this regard. However, the efficiency of the algorithms needs to be evaluated in a practical framework. Using a wide range of EAs increases the complexity of computation and hence the computation time. The standard form of the algorithms was thus applied on order to diminish computation time and reduce complexities in the analyses. It should, however, be noted that methods were not chosen randomly: there were some reasons for selecting these algorithms. The GA was selected due to its wide range of applicability in many branches of optimisation problems and the fact that it has even been coded in commercial mathematical software.

PSO has been tested in many optimisation problems and the training of neural networks in other problems. Thus, PSO was used as a classic EA. The SFLA was used due to its originality, meaning it is a good example for investigating animal-inspired algorithms. BBO was selected because of its different methodology and its successful application in environmental engineering. As a unique music-inspired algorithm, the HSA is special, and was thus selected to investigate the efficiency of unique EAs to train the ANFIS model. The DEA is a non-animal inspired algorithm that has successfully been applied in reservoir optimisation. The CA is an extension of the GA and was thus investigated to assess the efficiency of improved algorithms. IWO imitates the behaviour of weeds to look for the best environment for life and quick adaptation. Its origin is very different from all of the other algorithms, hence its inclusion in this study.

**Table 3-2-Main features of developed daily-based ANFIS model**

| Inputs | Number of MFs (inputs) | Type of MFs (inputs) | Outputs | Number of MFs (Output) | Type of MFs (Output) | Clustering method |
|---|---|---|---|---|---|---|
| **$Q_t$ -Daily Preceding Inflow (cms)** | 10 | Gaussian | $Q_{t+1}$ | 10 | Linear | Subtractive Clustering |
| **$P_t$- Daily recorded or forecasted rainfall(mm)** | 10 | Gaussian | | | | |
| **$W_t$- Daily Soil moisture (%)** | 10 | Gaussian | | | | |

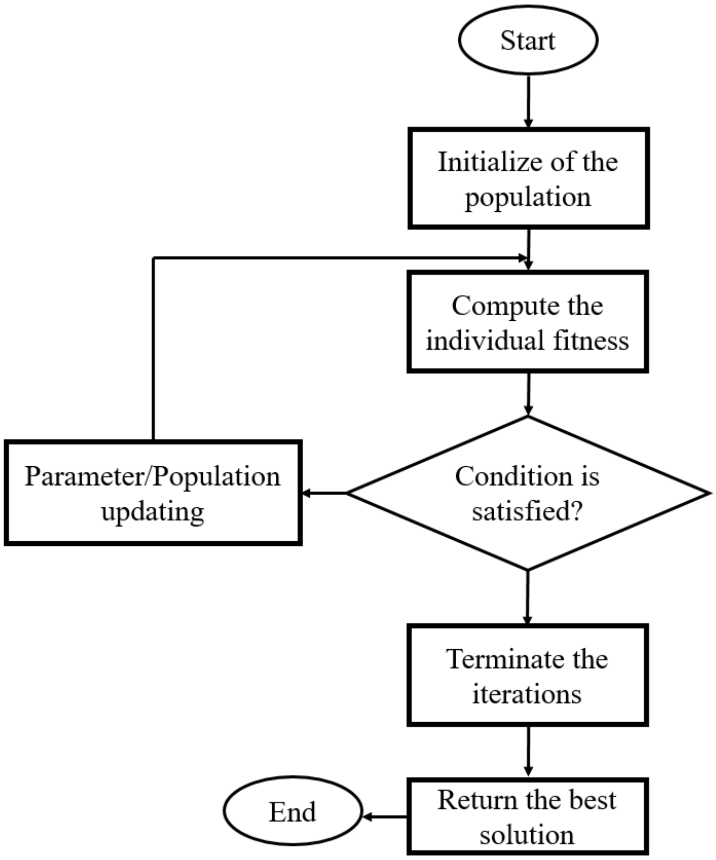



**Figure 3-5-General Flowchart of Evolutionary Algorithms**

### 3.2.4 Analysis of model performance

Four statistical indices were used to measure the performance of algorithms, including the root mean square error (RMSE) and Nash–Sutcliffe efficiency (NSE) (Gupta and Kling, 2011). Mathematical definitions of the RMSE and NSE for the present chapter are:

$$RMSE = \sqrt{\sum_{t=1}^{T} \frac{(O_t - M_t)^2}{T}} \quad (1)$$

$$NSE = 1 - \frac{\sum_{t=1}^{T} |M_t - O_t|}{\sum_{t=1}^{T} |M_t - O_m|} \quad (2)$$

where Ot, Mt and Om are respectively observed monthly inflow, modeled monthly inflow and average of observed monthly inflow. Moreover, reliability and vulnerability indices were calculated according to equations 3 and 4. These indices were inspired from system performance of reservoir operation to analyze data-driven inflow model of reservoir (Ehteram et.al, 2018a).

$$RI = \frac{\frac{\sum_{t=1}^{T} M_t}{T}}{\frac{\sum_{t=1}^{T} O_t}{T}} \tag{3}$$

$$VI = Max_{t=1}^{T} ABS\left(\frac{O_t - M_t}{O_t}\right) \tag{4}$$

### 3.3 Results and discussion

According to the proposed methodology, a daily-based ANFIS model was initially developed to simulate reservoir inflow. Then, developed models were used to forecast the performance of the model as a testing process. The simulation of daily reservoir inflow was not the purpose of the present chapter. However, changes of RMSE in a daily model would help to determine how many iterations might be adequate. Figure 3-6 shows the change in RMSE with respect to the number of iterations for all of the considered algorithms in the daily inflow model. Based on these results, increasing the number of iterations to more than 300 leads to negligible alteration in the RMSE. Based on this limited study, it thus seems that 300 iterations may be a representative number in typical cases to train ANFIS-based models to simulate reservoir inflow using EAs. In practical studies, it may be very important to reduce the computation time. In addition, for evaluation purposes where different scenarios need to be repeatedly tested, the computation time can be a very important consideration. As shown in Figure 3-6, the performance of the different algorithms was not the same. Some algorithms (e.g. the GA and PSO) showed very little change in RMSE, indicating high efficiency for the training process. The RMSEs of these algorithms was lower than those of the SFLA, CA and even the DEA. The performance of IWO was considerably affected by the number of iterations. Furthermore, the RMSEs of the algorithms at the beginning was different from their overall RMSE, which might be related to random population initialisation. The effectiveness or adequacy of the number of iterations thus needs to be investigated and tested before application to the simulation of inflows to reservoirs.

The standard deviation was also used to measure the performance of the developed daily model. This index is widely used in statistical studies. Comparing errors in estimations of the standard deviation is helpful to identify how a developed model could replicate observed data in terms of the distribution of forecasted or simulated data in the testing period. Some minor differences were found between the trends of the RMSE and the standard deviation, but the general trends could be considered similar, as shown in Figure 3-7. As already mentioned, the initial parameters (e.g. population size) were the same for all of the algorithms. The difference between the RMSE results in Figure 3-6 in the initial iterations is related to the random nature of the initial population: each algorithm selects initial candidates randomly and candidates are then improved during iterations to return the best responses. The main purpose of this study was continuous simulation of monthly long-term reservoir inflow. An ANFIS-based model was used to generate daily inflows. The daily outputs were then converted to monthly outputs by the averaging method. Measurement of system performance for monthly outputs was thus important to analyse the usability of the considered EAs for simulating inflows on a monthly scale.

The computed values of the four measurement indices (RI, RMSE, NSE and VI) are listed in Table 3-3. These results show that may not be a suitable option to train the ANFIS model for simulating inflow. For example, the NSE (as an appropriate index to evaluate the predictive skill of the model) of BBO was found to be −2.19, which means the predictive skill of the coupled BBO–ANFIS model was not robust enough to simulate inflows. In reality, NSE =0 indicates that the model has the same predictive skill as the mean of the time series in terms of the sum of squared errors. Thus, NSE = −2.19 is not acceptable in terms of predictive skill. In addition, the performance of the HSA was poor, with the computed values demonstrating that this algorithm should be excluded from the training process. That said, the HSA performed marginally better than BBO. The performances of the other algorithms were relatively close, although the weaker performance of the SFLA may be noted. It thus also seems that the SFLA may not be a strong contender for training the ANFIS-based model for reservoir inflows.

Although the computed indices demonstrate the unacceptable performance of some methods, further analysis was required to distinguish the other algorithms in order to select the best ones to train a data-driven model. Figure 3-8 shows the minimum, mean and maximum monthly simulated inflows obtained using the different algorithms compared with the recorded inflows. The observed data showed a significant range, between 4.5 $m^3/s$ and 95 $m^3/s$ approximately. A method that simulates minimum, mean and maximum values close to the observed data could indicate an acceptable method. In other words, if a model simulates extremely low or high flows in the simulated period, it will be an applicable tool to forecast inflows because it is able to predict extreme values, which is a challenging issue for reservoir management. Figure 3-8 corroborates the good performances of the GA, PSO and IWO in terms of the minimum, mean and maximum inflows. In other words, the GA, PSO and IWO can be considered suitable tools to train the ANFIS-based model of inflow. The performance of these was similar.

Figure 3-9 shows the simulated inflow time series of the Ross River reservoir for the testing period using the different algorithms. The SFLA, HSA and BBO were excluded due to their very weak performance. The figure demonstrates that the GA, PSO and IWO would provide relatively similar performance in the simulation of inflows. However, the performance of the GA, PSO and IWO may not be fully acceptable in terms of simulating inflows of extreme peaks or nadirs. The outputs from these three methods in the initial months of the simulation were significantly higher than observed values. However, by the fourth or fifth month, the modelled and observed values were close. These three models simulated local peaks during the simulation period properly. However, performance of the models in simulating the absolute maximum point was not satisfactory, with a remarkable difference between the modelled and observed inflows. It can be stated that the developed daily ANFIS-based model using GA, PSO and IWO as EAs for training provided appropriate simulations in the testing period. The ANFIS-based daily stream flow model was developed to simulate monthly long-term reservoir inflow based on rainfall data. Recorded rainfall data were used for testing. In other words, an ideal scenario (equivalent to perfectly forecasted rainfall) was considered in testing period. In future applications, instead of recorded rainfall, forecasted rainfall may be used to transform the model into an inflow forecasting model. The developed model only uses an approximate relationship between soil moisture and the number of days after a rainfall event and inflow on the first day of simulated period. This use of minimum data is an advantage of the proposed model.

The current results were compared with the results of a previous study. Awan and Bae (2014) developed an ANFIS-based model for simulating long-term inflow to reservoir and used a hybrid algorithm to train the model. Thus, investigation of their results is helpful in comparing the abilities of a hybrid algorithm and EAs to train ANFIS models. The main challenge in applications of data-driven models is to simulate peak points in inflow time series. According to Awan and Bae (2014), the error could be 0–50%. In contrast, the outputs of the present chapter showed a maximum error of 30% in simulating peaks. There are two reasons for the improvement shown by the model proposed in the current study. Firstly, developing the model in accordance with daily data and then converting to monthly inflow output over a long-term period enhanced the model performance model. Secondly, the EAs used for training improved the search for a better optimal solution. The focus of the present chapter should be noted as this may be helpful for further applications. An ANFIS-based daily stream flow model was developed to simulate monthly long-term reservoir inflow. The model was able to simulate reservoir inflow based on rainfall data. Recorded rainfall data were used in the testing period. In other words, an ideal scenario (equivalent to perfect forecasted rainfall) was considered in the testing period. However, if a robust forecasting rainfall model were to be coupled with the developed model, it would be able to forecast reservoir inflow in future periods. Hence, the main application of the developed model could be to forecast reservoir inflows in the near future, which is useful for reservoir management. In addition, the proposed model could be coupled with climate change models to predict inflow in the farther future, incorporating how rainfall may be impacted by climate change. The present chapter indicates that, at least for the illustrative test scenarios, the performance of the model for simulating reservoir inflow improved with the use of EAs. The utility of using GA, PSO or IWO to train an ANFIS-based model to simulate monthly long-term reservoir inflow was established.

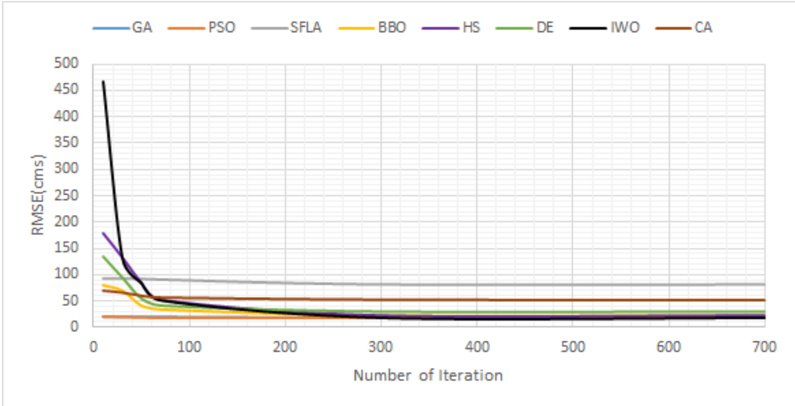



**Figure 3-6- Impact of iterations on RMSE of daily based ANFIS model**

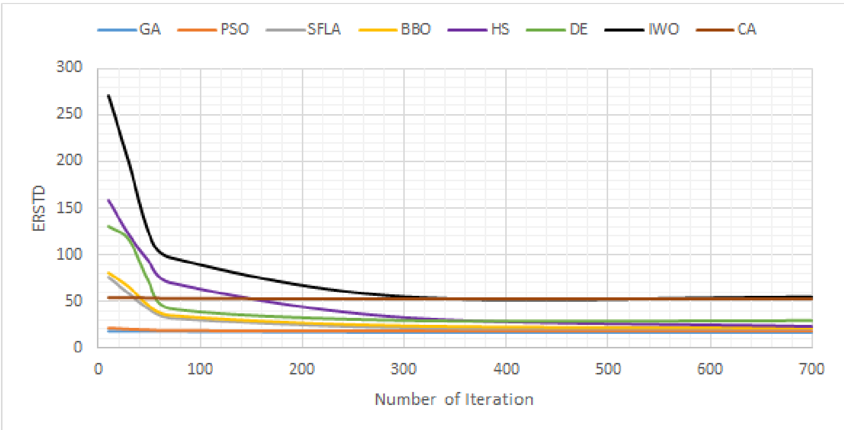



**Figure 3-7- Impact of iterations on error of standard deviation in daily based ANFIS model**

**Table 3-3-Model performance analysis for different training methods**

| | BBO | IWO | CA | DE | HS | SFLA | GA | PSO |
|---|---|---|---|---|---|---|---|---|
| RI | 0.21 | 0.95 | 0.96 | 1.01 | 0.60 | 1.05 | 0.93 | 0.98 |
| RMSE | 192.272 | 73.470 | 75.467 | 81.187 | 97.370 | 85.874 | 76.195 | 73.500 |
| NSE | -2.19 | 0.53 | 0.51 | 0.43 | 0.18 | 0.36 | 0.50 | 0.53 |
| VI | 0.96 | 3.06 | 7.51 | 5.92 | 4.12 | 8.01 | 3.32 | 3.21 |

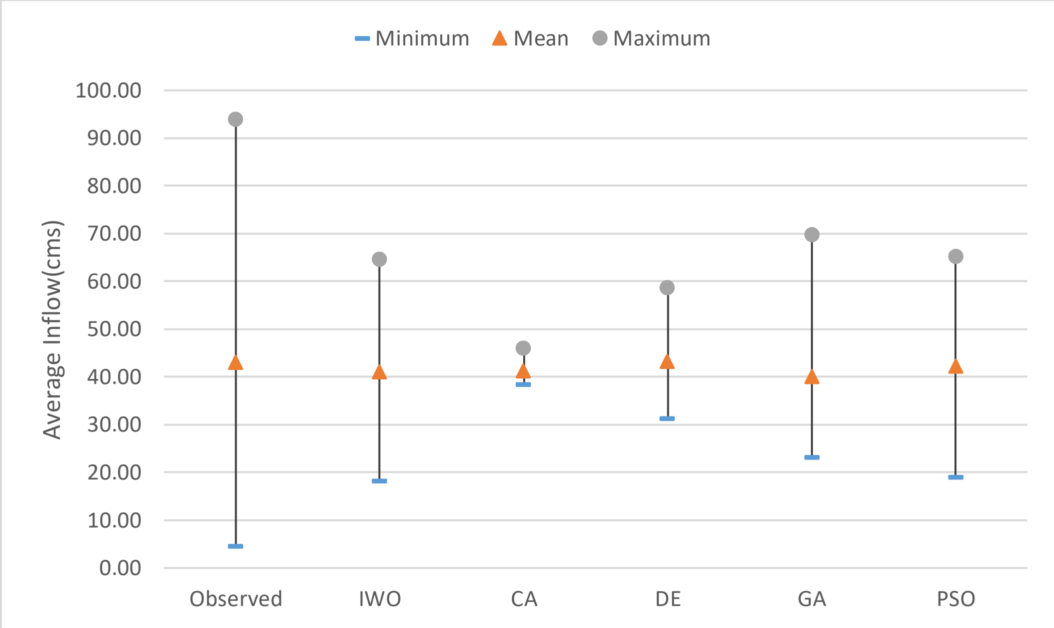



**Figure 3-8- Minimum, mean and maximum of monthly average inflow by different algorithms compared with observed data**

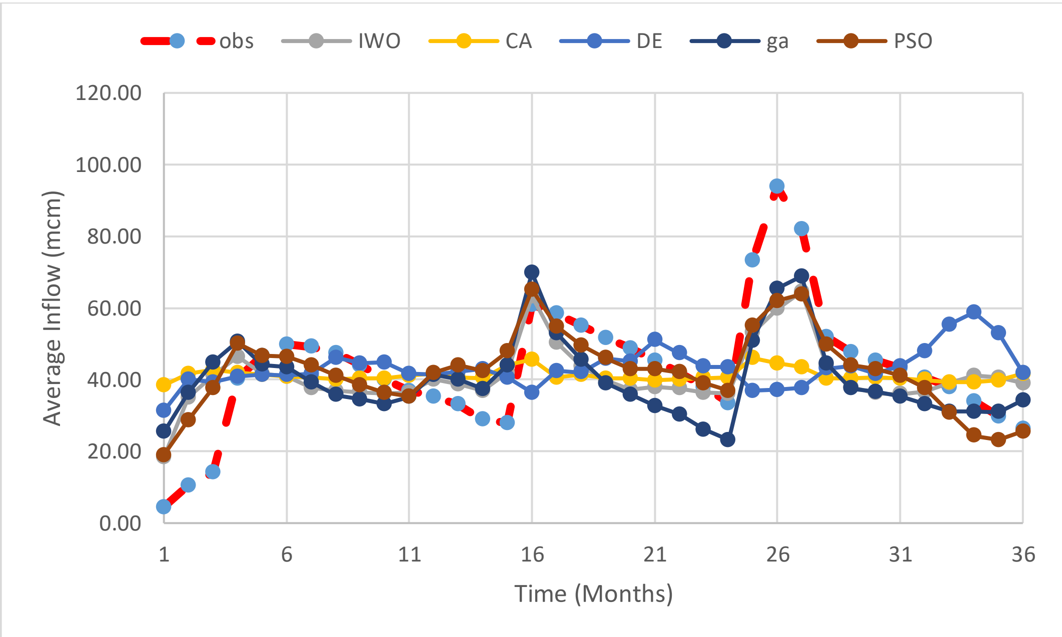



**Figure 3-9- Inflow time series (observed and selected algorithms) in testing period**

## 3.4 Summary

The contribution of the present chapter was to improve the data driven models for forecasting reservoir inflow. Data-driven models provide upgradeable environments to simulate inflow to reservoirs. An important aspect in the development of an adaptive neural fuzzy inference system (ANFIS) model is to choose the correct procedure (i.e. efficient and effective) to train the model. In this study, a daily timescale ANFIS-based model was developed to simulate aggregated monthly long-term inflow to the Ross River reservoir in northern Queensland, Australia. The suitability of different evolutionary algorithms (EAs) was evaluated to train an ANFIS-based model, including a genetic algorithm (GA), particle swarm optimisation (PSO), shuffled frog-leaping algorithm, biogeography-based optimisation, harmony search algorithm, differential evolution algorithm, invasive weed optimisation (IWO) and a cultural algorithm. Four indices – the root mean square error, Nash–Sutcliffe efficiency, reliability index and vulnerability index – were used to measure the performance of the model. It was found that application of either IWO, GA or PSO provided accurate simulated inflow time series. The outputs obtained using the other EAs were not sufficiently accurate. Use of a coupled EA–ANFIS-based model was found to improve the accuracy of simulating long-term monthly inflow compared with other models used in a few previous recent studies.

# Chapter 4: Environmental operation of diversion dams considering environmental flow (a single- objective algorithm)

Full contents of this chapter have been published and copyrighted, as outlined below:

Sedighkia, M., Abdoli, A. and Datta, B., 2021. Optimizing monthly ecological flow regime by a coupled fuzzy physical habitat simulation–genetic algorithm method. Environment Systems and Decisions, pp.1-12.

## 4.1 Introduction

Rivers have a vital role for life of many species in the world. In other words, they are one of the main water resources to supply agricultural, drinking and industrial water demands. Conflict between human's water demand and environmental requirements was the origin of environmental flow. Environmental flow has been defined as essential flow regime that may guarantee suitable ecological status of river ecosystem (Tharme 2003). As a general classification of methods, they can be classified into four groups including hydrological methods, hydraulic rating methods, physical habitat methods and holistic methods (Jowett 1997; Tharme 2003). Previous studies corroborated that physical habitat methods with focus on regional ecological values provide better impact assessment at a specific site (Acreman and Dunbar 2004). Instream flow incremental methodology (IFIM) defines impact assessment framework by an integrated habitat simulation method to assess environmental flow (Payne and Jowett 2013). Moreover, IFIM was the first method or process that considered fishes as lawful users of river flow (Stalnaker 1994). The core of IFIM is physical habitat simulation by univariate habitat method. Different studies reviewed different aspects of applying physical habitat simulation. Ability of physical habitat simulation in the dynamic assessment of habitats is authenticated by previous studies (Sedighkia et al. 2017). Jowett and Duncan 2012 studied application of one-dimensional and two-dimensional hydraulic modelling in the hydraulic habitat simulation. Results demonstrated that one-dimensional hydraulic simulation provides proper hydraulic results. However, using two-dimensional hydraulic modelling might be complex and difficult. Papaioannou et al. 2020 highlighted that the result of two-dimensional habitats hydraulic modelling is sensitive to the mesh resolution. PHABSIM is known to simulate physical habitats and assessment of environmental flow in rivers. However, there were some critiques regarding univariate method of PHABSIM in hydraulic habitat simulation. Hence, development of fuzzy multivariate approach was an important step to improve univariate habitat model (Noack et al. 2013). CASIMIR software developed fuzzy-based hydraulic habitat simulation. Its main advantage is to utilize expert's opinions to develop physical habitat criteria. In other words, Fuzzy approach is able to consider expert's knowledge in the development of habitat fuzzy rules (Jorde et al. 2001; Noack et al. 2013).

It is required to review on the recent studies that focussed on the importance of environmental flows in ecosystem conservation. Kuriqi et al. 2020 highlighted the importance of environmental flows for sustainable expansion of run-of-river hydropower. Kuriqi et al. 2019 Introduced Downstream Diversion Index (DDI). They developed a practical approach to estimate environmental flow releases and alteration due to water diversion for energy production. Moreover, Suwal et al. 2020 utilized NSGA-II algorithm to optimize cascade reservoir operation for improvement of environmental flow management. Suwal et al. 2020 evaluated hydrological methods for environmental flow assessment using the indicator of hydrological alteration. Furthermore, studies pointed out that physical habitat simulation is an applicable method for environmental flow assessment and river ecosystem management (Hajiesmaeili et al. 2014). Owing to complexities of water resource management, optimization is an appropriate solution to improve management of water consumption and infrastructures. Application of optimization methods has extensively been investigated in the reservoir operation which defined loss function as objective function and some constraints such as storage constraint to optimize release and storage (Datta and Houck 1984). Development of evolutionary algorithm was effective to improve optimization solutions in the water resource management (Ahmad et al. 2014). Many evolutionary algorithms have been utilized for reservoir operation optimization (e.g. Afshar et al. 2011; Sharif and waldlaw 2000; Ehteram et al. 2018a). It seems that using evolutionary algorithms is useful for other optimizations such as environmental flow optimization.

Previous studies considered environmental flow in the water resource optimization (e.g. Yin et al. 2012; Cai et al. 2013; Horne et al. 2017). However, they did not focus on fuzzy physical habitat simulation as one of the reliable methods to quantify environmental requirements of the river ecosystem. In other words, using fuzzy physical habitat simulation might provide a robust framework to simulate and optimize environmental flow. It should be noted that using fuzzy physical habitat simulation is not flexible. In fact, it is not able to optimize environmental flow and water demand in the study area. Hence, development of a simulation–optimization framework might be necessary to improve applicability of fuzzy physical habitat simulation method.

The present chapter proposes and evaluates a novel framework to optimize monthly environmental flow regime at downstream of diversion dams as one of the important hydraulic structures in the rivers. Reliable environmental flow methods such as physical habitat simulation lack optimization framework of environmental flow and water demand. Simultaneous supply of water demand and environmental flow is challenging. Hence, an optimization framework is essential. The main objective of the present chapter is development of a novel simulation–optimization framework to assess environmental flow regime in which the fuzzy hydraulic habitat method simulates physical habitats and the genetic algorithm optimizes environmental flow in terms of physical habitat suitability and water demand loss. Two aspects should be noted regarding novelty of the proposed method. First, it proposes a novel application of physical habitat simulation in the water resource engineering to optimize environmental requirements and water demand. Secondly, the new form of loss functions and objective functions are developed to improve performance of diversion dam operation.

## 4.2 Application and methodology

### 4.2.1 Study area, problem definition and field studies

Haraz River is one of the important rivers in Tehran and Mazandaran provinces in Iran that originates from the Alborz mountain range towards the Caspian Sea. This river has a significant role for supply of water demands in these provinces. Several tributaries along the river enhance river flow. Hence, different hydraulic structures have been constructed to supply water demands. Water supply of new developed areas is crucial for local government due to increasing population in this river basin. Development of a combined urban and industrial area was the purpose for construction of a new diversion dam. This diversion dam supplies drinking and industrial water demand in new city. However, environmental impact at downstream is highlighted by the department of environment. Main concern is protection of the Brown trout habitats at downstream. Brown trout is a protected species by the department of environment and is in red list of International Union for Conservation of Nature.

Environmental flow is vital for maximum protection from the brown trout habitats. However, supply of water demand is crucial as well. Hence, optimization of water allocation should be considered in project planning. It, however, seems that there is a serious conflict between water supply and environmental flow. On the one hand, local government requested to divert maximum flow to supply water demands. On the other hand, reducing flow in the river might damage the Brown trout habitats that decrease fish population consequently. As a result, it is important to allocate water for demands and environment optimally. The Brown trout is a sensitive native species in this basin. Thus, it could be an appropriate index to assess environmental flow (Niksirat and Abdoli 2009). In this study, adult fish was considered in the sampling and developing habitat suitability criteria. The fish observations were carried out during one summer and one winter. Adult fish was selected due to considerable population in the river habitats which means it can be a good environmental index to show the impacts of abiotic factors. Figure 4-1 displays study area. Simulated river reach is at downstream of diversion dam.

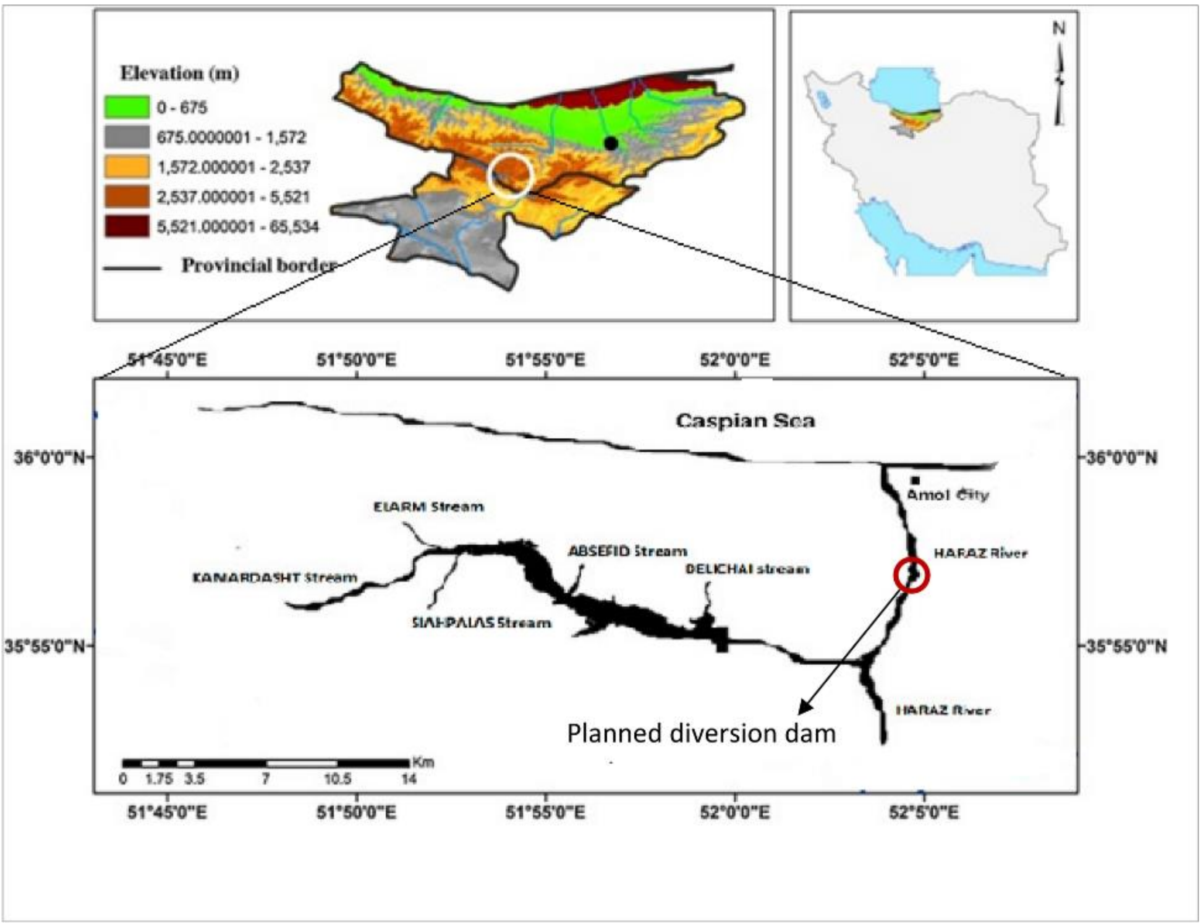



**Figure 4-1-Study area**

Field studies is a requirement to develop habitat suitability criteria. The most important step in the field studies is fish sampling at microhabitats to develop habitat fuzzy suitability criteria. Different methods have been presented for fish sampling in the microhabitats. As general classification, these methods are classified in two groups including direct methods in which direct observation of fishes is used such as video telemetry methods and indirect methods such as electrofishing. Advantages and drawback of different methods have been discussed in the literature (Harby et al. 2004). We applied electrofishing to sample fish at microhabitats. The main reason of this choice was experienced ecologists in our team to apply this method. Depth, velocity and substrate were measured simultaneously at each microhabitat.

Propeller that is one of the best options for river habitat studies carried out velocity measurement by 2-points method (Harby et al. 2004). Measurement of depth was carried out by metal ruler due to limited depth in stream that was between 5 and 100 cm. Substrate was measured by capturing photo of bed in each microhabitat. Captured photos were converted to real diameter of each particle by image processing software. Then, mean diameter in each point was estimated. Owing to importance of reducing injuries to fish, electrofishing was used in low voltage. More than 95% of captured fish was returned to habitats during field studies. Surveying river cross-sections and measurement of discharge at each cross-section

were other steps in the field studies. The proposed method by Barton et al. 2004 was utilized to survey cross-sections and measurement of discharge was carried out by subdivision method.
Resolution of used data should be presented in this section. Recorded flows were used in the monthly scale due to focus on optimization of monthly ecological flow regime in the present chapter. The cross-section data are another requirement for the simulation of physical habitats in the simulated river reach. We surveyed cross-sections in close distances. In the considerable changes of river geometry, cross-sections were surveyed at each 30 m. In contrast, distance between cross-sections was considered 60 m for the uniform river geometry. Total length of simulated river reach was 1000 m.

### 4.2.2 Habitat loss function

Fuzzy hydraulic habitat simulation was used to simulate habitats of the river reach. The most important advantage of fuzzy logic approach for simulation of hydraulic habitat is the ability to consider expert's opinions. Hence, habitat suitability fuzzy rules were developed based on field observations and expert opinions. More details on simulation are described in the literature (e.g. Boavida et al. 2014). Hydraulic habitat simulation generally simulates habitats based on a target species. In the present chapter, Brown trout was selected based on previous studies on the Haraz river basin (Sedighkia et al. 2019). The most important output of hydraulic habitat simulation is weighted useable area (WUA). This parameter originally defines available useable area in each 1000 m of river that could be a good criterion of available useable habitats for fishes (Waddle 2001). We used reversed WUA (normalized habitat loss) as habitat loss function. In fact, increasing normalized habitat loss (NHL) reduces suitable habitats. In this study, NHL is defined as area of unsuitable habitats to total available habitats. Reducing river flow by diversion project might remarkably decrease habitat suitability especially during dry months.

### 4.2.3 Project loss function

Diversion dam project was planned to supply water demand of residential and some industrial activities that would be developed in future years. Initial estimation on water demand in the target point showed that totally 1.72 MCM is maximum daily need for supply of all the water demands. However, it is clear that supply of ecological flow can affect water supply. Reduction of water supply was defined as the loss function of the diversion project. A linear normalized loss function was utilized. Figure 4-2 displays the proposed loss function. MF is monthly flow (MCM) and NPL is normalized project loss (%). In this study, NPL is defined as actual water supply by the project to maximum water demand.

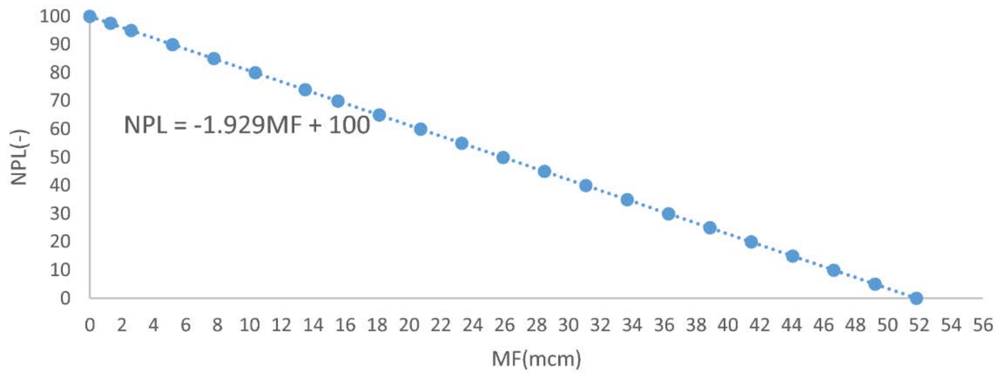



**Figure 4-2- Normalized project loss function**

### 4.2.4 Optimization model

The first step for development of optimization model is definition of objective function. This function minimizes distance between NHL and NPL. In other words, this new form of objective function may guarantee a balance between water demand supply and environmental flow.

$$Minimize(OF) = \sum_{t=1}^{T} (NHL_t - NPL_t)^2, \qquad (1)$$

where $NHL_t$ and $NPL_t$ are monthly habitat and project loss, respectively. T is time horizon. Moreover, two constraints were considered in the optimization process including minimum WUA and maximum NPL. The complexity of objective functions in the water resource management demonstrated that using evolutionary algorithms is a necessity to solve optimization problems (Ehteram et al. 2018b). The genetic algorithm (GA) is one of the popular and known techniques regarding complex objective functions. This algorithm is originally a Darwinian natural selection process (Whitley 1994) which has been widely applied in some water resource management problems such as reservoir optimization. Flowchart of the genetic algorithm is shown in figure 4-3. Two indices were used to measure diversion system performance including reliability and vulnerability indices (Ehteram et al. 2017). In the present chapter, reliability index and vulnerability index were calculated based on Eqs. 2 and 3, respectively,

$$\alpha = \frac{\sum_{t=1}^{T} O_t}{\sum_{t=1}^{T} D_t} \qquad (2)$$

$$\gamma = Max_{t=1}{}^{T}\left(\frac{D_t - O_t}{D_t}\right), \qquad (3)$$

where D is maximum water demand of diversion dam project and O is optimal release for water demand. Each optimization method has some limitations that should be noticed for further applications. The first limitation of the proposed method is high costs of required field studies to implement in the practical projects. In other words, fish observation and measurement of hydraulic parameters might be expensive and time consuming. It should be noted that lack of sufficient field studies might weaken accuracy of habitat fuzzy rules. Moreover, development of water demand loss or project loss function might be complex in some case studies. It might increase computational complexities of the developed optimization system.

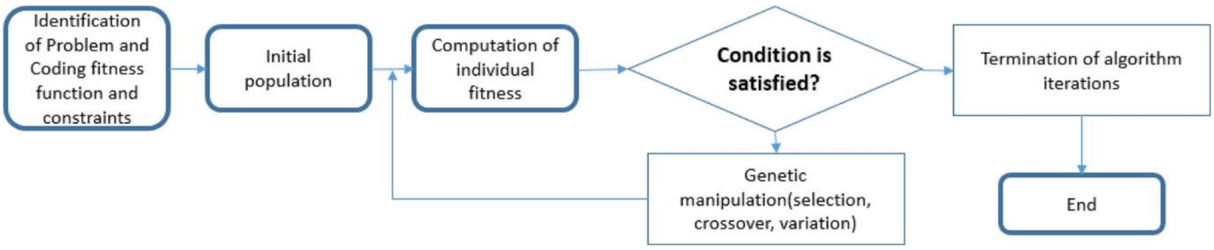



**Figure 4-3- Genetic algorithm (GA) flowchart**

## 4.3 Results and discussion

### 4.3.1 Fuzzy hydraulic habitat simulation

Developed degree membership for three main physical factors including depth, velocity and substrate are shown in figure 4-4. Based on previous studies, trapezoidal degree membership are common form in hydraulic habitat simulation (Noack et al. 2013). Substrate was defined as channel index as displayed in Table 4-1. By increasing channel index, particle bed size would be added. Development of degree of fulfilment function is one of the essential steps for hydraulic habitat simulation, shown in figure 4-5.
Fuzzy rules are the most sensitive inputs for habitat simulation. Developed fuzzy rules are shown in Table 4-2. According to developed fuzzy rules, it demonstrates that suitability of microhabitats is more sensitive to alteration of flow velocity. For instance, if flow velocity is high habitat suitability will be low which sounds logical because flow velocity has a significant role in energy consumption by fish. Hence, high flow velocity will consume considerable energy for swimming. Deep habitats might provide safe place for the Brown trout. If flow velocity is tolerable, increasing depth will enhance suitability of microhabitats. Substrate will provide a suitable environment for many activities of fish, for example, searching for food and reproduction. Coarser particles could provide better environment for biological activities of the Brown trout.

**Table 4-1- Channel index guideline**

| Channel index guideline | |
|---|---|
| Channel properties | **Channel index** |
| **Plant/Organic** | 1 |
| **Mud/soft clay** | 2 |
| **Silt** | 3 |
| **Sand** | 4 |
| **Gravel** | 5 |
| **Cobble** | 6 |
| **Boulder** | 7 |
| **Bedrock** | 8 |

**Table 4-2- Developed habitat fuzzy rules**

| Rule code | Depth | Velocity | Substrate | Habitat suitability |
|---|---|---|---|---|
| **BR1** | M | L | M | M |
| **BR2** | H | L | M | M |
| **BR3** | L | L | M | L |
| **BR4** | H | M | H | H |
| **BR5** | L | M | H | H |
| **BR6** | M | M | H | H |
| **BR7** | H | H | L | L |
| **BR8** | M | H | L | L |
| **BR9** | L | H | L | L |
| **BR10** | M | M | M | M |
| **BR11** | L | M | M | M |
| **BR12** | H | M | M | M |
| **BR13** | M | H | M | L |
| **BR14** | L | H | M | L |
| **BR15** | H | H | M | L |
| **BR16** | L | L | L | L |
| **BR17** | M | L | L | L |
| **BR18** | H | L | L | M |
| **BR19** | L | L | H | M |

| | | | | |
|---|---|---|---|---|
| **BR20** | M | L | H | M |
| **BR21** | H | L | H | H |
| **BR22** | M | M | L | H |
| **BR23** | H | M | L | H |
| **BR24** | L | M | L | M |
| **BR25** | L | H | H | L |
| **BR26** | M | H | H | L |
| **BR27** | H | H | H | L |

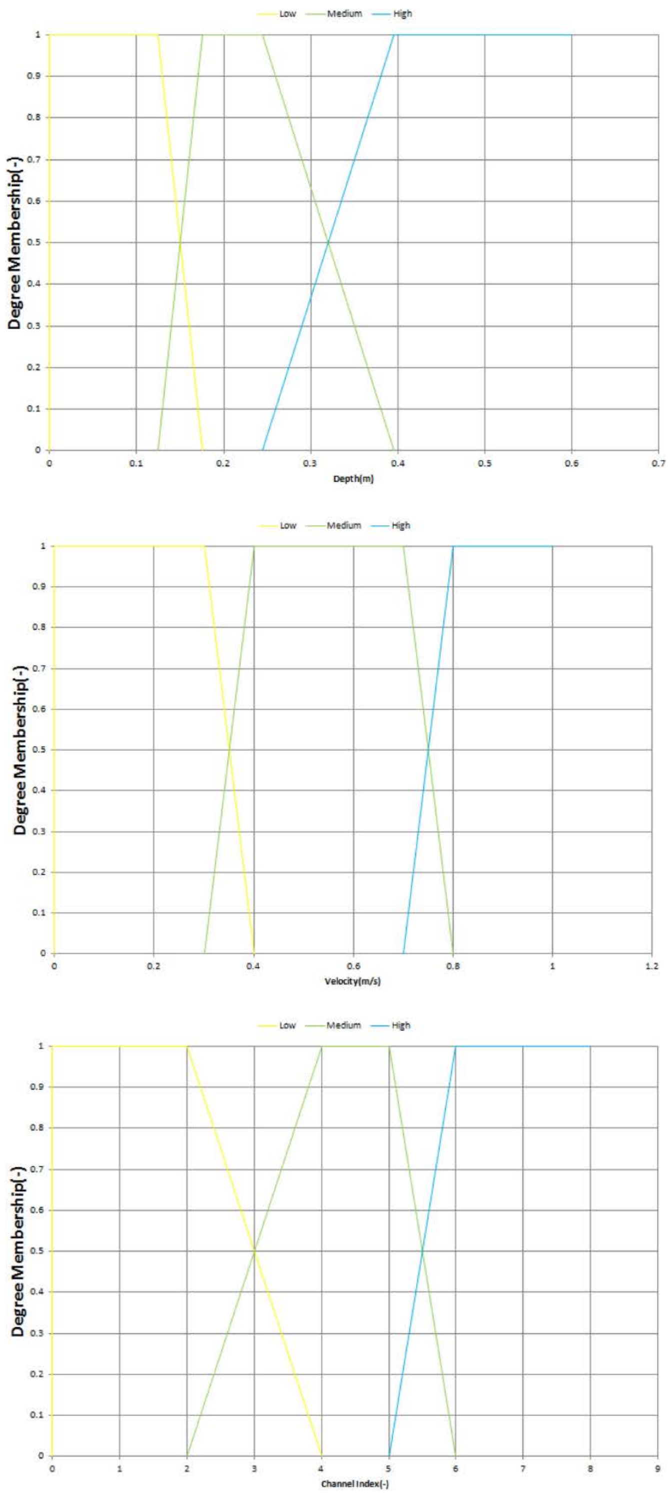



**Figure 4-5- Developed degree membership functions**

Changes of WUA in different flows are shown in figure 4-6 that reveal alteration of suitability by increasing discharge. Increasing flow affects suitability of habitats. It, however, should be noted that this effect is not constantly positive or negative. Maximum available useable area is provided in monthly flow of 14 to 17 MCM that is approximately 2800 $m^2$ in each 1000 m. Changes of flow between 0 to 14

MCM quickly alter suitability of habitats. Moreover, changes of river flow between 17 to 40 MCM reduce physical suitability. It is, however, clear that more flow provides sustainable physical habitat suitability in the studied reach. Habitat loss function is shown in figure 4-7. Based on ecological expert's opinion for protection of 50% of fish community in all of the months, minimum NHL was considered 55%, which was used in the optimization model. It should be noted that main assumption of physical habitat simulation is linear relationship between useable area and biomass. Hence, WUA can define biomass in the river reach.

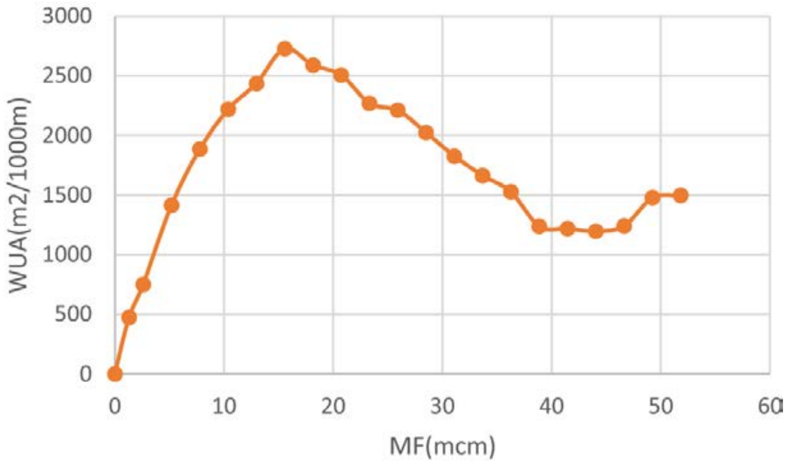



**Figure 4-6- WUA respect to monthly flow**

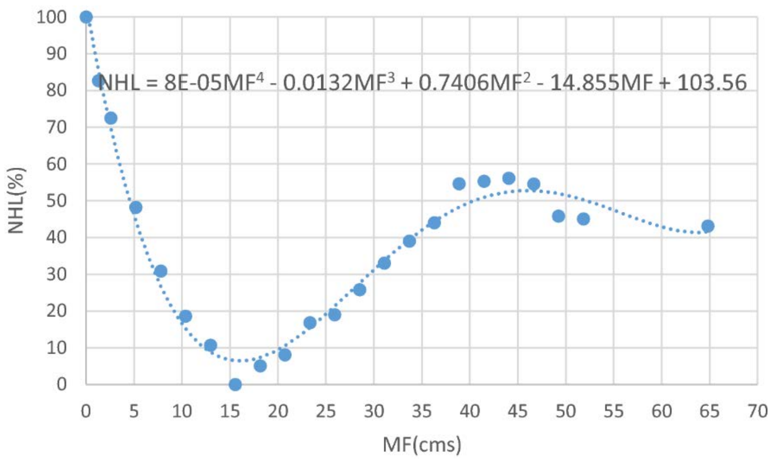



**Figure 4-7- Habitat loss function used in optimization model**

### 4.3.2 Optimization model

Figure 4-8 shows objective function value with respect to the number of generation in the GA. According to this Figure, its value does not change for more than 200 generations in the optimization. In other words, computational time decreases logically without increasing errors by reducing the number of generations. Figure 4-9 shows the ISV, TV and OSV in each month, which are optimized instream volume, total volume and optimized offstream volume. Optimal regime provides fair water consumption between users of diversion project and users at environment. Analysis of outputs is essential for better understanding on the proposed water allocation. January to March and September to December are dry months in the natural river flow regime. Optimized instream flow proposes minimum habitat suitability in these months. If instream flow increases, project loss will considerably increase. Hence, optimization model increased offstream flow by keeping minimum physical habitat suitability. In the wet months, optimization model increased instream flow dramatically. In other words, physical habitat suitability is increased.

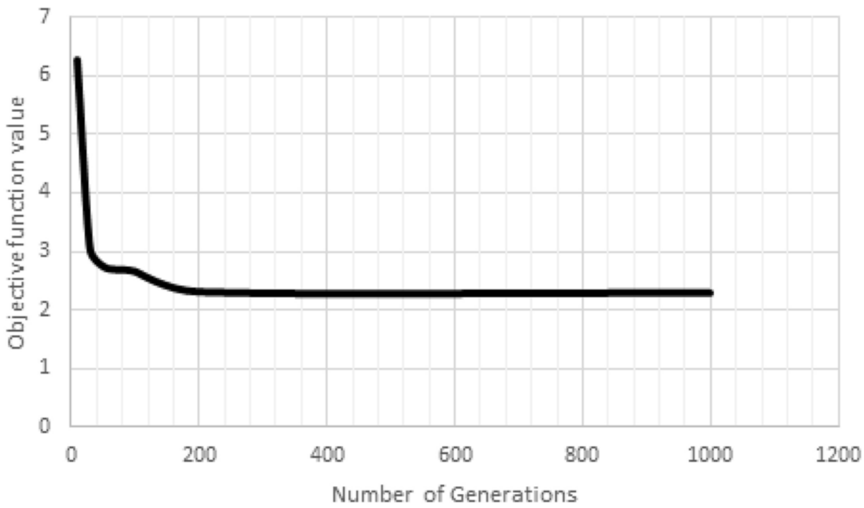



**Figure 4-8- Habitat loss function used in optimization model**

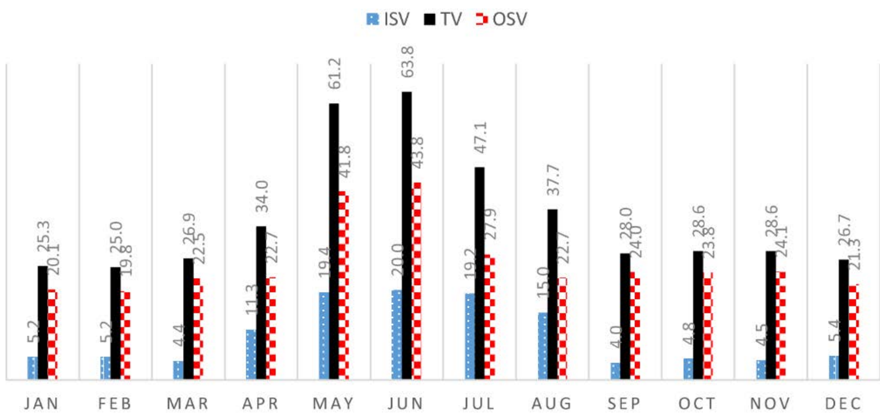



**Figure 4-9- Optimized environmental flow regime by simulation–optimization method (million cubic meters)**

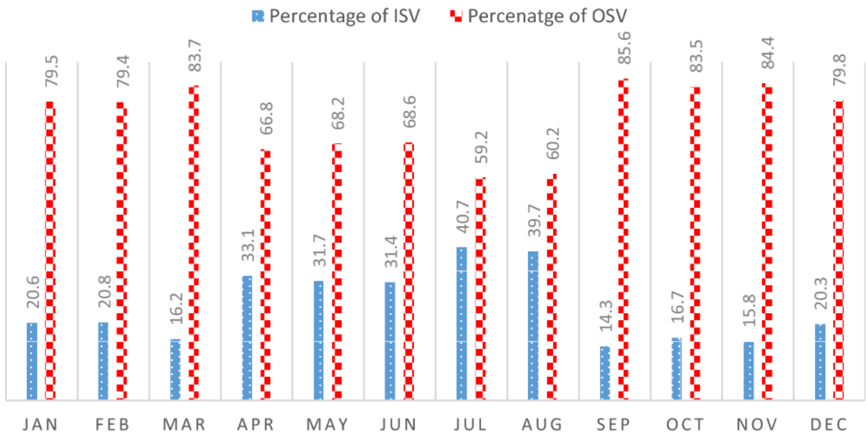



**Figure 4-10- Instream and offstream flow based on percentage of mean annual flow (Percentage of MAF)**


**Figure 4-11- Comparison of optimized environmental flow regime and Tennant's recommendations in environmental flow regime assessment in million cubic meters**

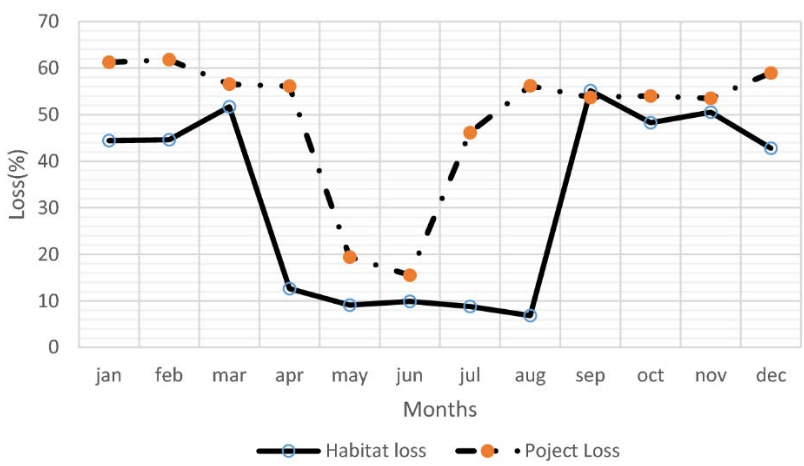



**Figure 4-12- Monthly loss time series due to implementation of proposed simulation–optimization framework**

**Table 4-3- Measurement indices**

| Index | Reliability | Vulnerability |
|---|---|---|
| **Value** | 80% | 34% |

One of the criteria in the assessment of environmental flow is to define environmental flow regime based on percentage of mean annual flow. Tennant method as one the basic methods assesses environmental flow based on percentage of MAF. This method is used in study area to evaluate environmental flow currently. Figure 4-10 displays MAF percentage of instream and offstream flow in different months. Minimum instream flow is 14.3% in September. Meanwhile, maximum of instream flow is in July (40.7%). One of the most important drawbacks of previous studies by hydraulic habitat simulation and similar approaches is lack of optimization process. In fact, they independently proposed a regime for environmental flow that might not be feasible due to water demand considerations. The most important problem of water allocation in many drought regions is lack of enough waters for all of the users. IFIM proposed a negotiation based method to assess final environmental flow regime in rivers. It might not be applicable in many case studies especially in developing countries due to high cost and lack of enough experts. Hence, fair water allocation should be noted in the definition of environmental flow regime in rivers. This research work proposes an applicable framework in this regard. Initial assumption in the case study was to apply Tennant method for assessing environmental flow regime because minimum estimation of Tennant could provide sufficient water for the requested water demand. Hence, system performance of optimal water demand was measured based on initial assumption. It should be considered that comparison of results with Tennant method clarifies advantages of the proposed method to assess environmental flow.

Tennant 1976 proposed different stages of environmental flow that were based on river status. Two main stages of including poor and outstanding statuses were considered. Poor or minimum recommendation is considered as minimum environmental flow regime. Figure 4-11 shows the results of current study, poor and outstanding statuses, respectively. The present chapter provides a balance between environmental requirements and water demand. In other words, minimum environmental flow by Tennant method is not sufficient to protect habitats. However, outstanding environmental flow might increase conflict for supply of water demand. Using hydraulic habitat simulation method without optimization process will rise challenges between environmental managers and stakeholder because it is not flexible in the assessment of environmental flow. For example, optimum point of WUA is between 15 and 17 MCM for monthly water allocation. It is, however, clear that this flow could not be supplied in the dry seasons because this regime is not flexible for supply of water demand. Application of hydraulic habitat simulation methods without optimization model cannot consider fair water allocation.

Analysis of habitat loss and project loss is a useful tool to investigate consequences of using proposed simulation–optimization model. Figure 4-12 displays monthly loss time series. Habitat and project losses are considerable in the dry months because enough water for all of the users is not available. However, optimization model could balance losses. Both losses are significantly reduced during wet months. It can, however, be seen that due to non-linear changes of habitat loss function, it is less than project loss in some months such as April, July and August. As a result, simulation–optimization model defines instream flow need by estimation on the effect of flow alteration on useable habitats. Reliability index was computed based on Eq. 2. In this equation, demand was considered based on initial plan of project, i.e. 10% of MAF. For environmental flow, vulnerability index was calculated based on Eq. 3. Their results are displayed in Table 4-3. According to Table 4-3, reliability index is relatively high and proposed method can reliably support water demand. Vulnerability index is, however, relatively high that must be considered in the final plan of project. A point should be noted in the discussion is why the proposed optimization algorithm is efficient and advantageous. For example, another option for optimization is to apply multi-objective optimization for habitat loss function and project loss function. It should be noted that computational complexities, i.e. time and memory requirements are effective issues for using optimization algorithms. Multi-objective algorithms such as multi-objective genetic algorithm might increase computational complexities due to using complex computations. It might be a problem for covering long-term simulation period and numerous optimizations. Hence, combined objective function in the present chapter would be advantageous in terms of computational complexities. Moreover, limited number of multi-objective algorithms have been developed and coded. However, many single-objective evolutionary algorithms have been developed which are freely available. Efficiency of different algorithms may be very different. Developed form of optimization model makes it possible to use many other evolutionary algorithm to investigate the efficiency of different algorithms. A long list of this type of evolutionary algorithms has been addressed in the literature.

It is required to review and discuss on the main finding of the present chapter and previous related studies. Jorde et al. 2001 demonstrated that increasing depth and substrate increase habitat suitability as confirmed by this study. Mouton et al. 2011 developed fuzzy rules based on the data-driven model. Similarly, they demonstrated that high flow velocity significantly reduces habitat suitability. Results demonstrate that optimizing environmental flow at the downstream of diversion dams is required because available water in the river might not be sufficient to supply environmental requirement and water demand simultaneously. Hence, a simulation–optimization framework for environmental flow is essential. We applied fuzzy physical habitat simulation to develop habitat loss function that was efficient because the proposed method optimized habitat loss that was less than 50% in the most of months. Moreover, an optimal environmental flow regime was developed based on the results. This optimal regime is robust compared with the Tennant method as current used method in the study area because it was more than the minimum recommended flow by Tennant in all of the time steps that demonstrate the proposed method is able to provide minimum protection for habitats. Moreover, it was close to outstanding ecological status when the available flow of river is remarkable. In other words, it is able to protect habitats as much as possible. Furthermore, the proposed optimization framework was robust in terms of reliability of water supply because reliability index was 80% that demonstrates this novel method is able to supply 80% of maximum water demand in the study area. However, vulnerability of water supply is relatively considerable. It is required to consider other alternatives of water supply for months in which vulnerability index is high. It should be noted that physical habitat approach is known to assess environmental flow. However, it is inflexible to optimize environmental flow regime for the case studies in which water scarcity might increase challenges for simultaneous supply of water demand and environmental flow. The proposed framework converted fuzzy physical habitat simulation to a simulation–optimization method in which the genetic algorithm was utilized as optimization method. Moreover, it is required to investigate main findings of the present framework compared with recent studies. Suwal et al. 2020 focussed on the different hydrological methods of environmental flow. The results indicated that vulnerability of 10% MAF might be considerable. The present method assessed environmental flow more than 10% MAF in all of the time steps. Hence, reliability of results could be confirmed based on the recent studies.

## 4.4 Summary

The present chapter proposes and evaluates a fuzzy hydraulic habitat simulation–genetic algorithm method to optimize environmental flow regime with focus on a diversion dam project. The proposed method develops an objective function that minimizes the difference between habitat loss and water demand or project loss. Fuzzy physical habitat simulation was used to develop habitat loss function. Moreover, the genetic algorithm was utilized as optimization method. Based on results, minimum available environmental flow in dry seasons was approximately 15% of mean annual flow. However, its maximum would increase to 40% of mean annual flow in wet seasons. Reliability and vulnerability indices for supply of water demand were 80% and 34%, respectively, in the case study. Results of the proposed framework were compared with the Tennant method to demonstrate abilities for optimizing environmental flow. The most important advantage of proposed method is minimization of conflict between stakeholders and environmental advocators. In other words, the proposed method might be able to minimize negotiations to assess environmental flow regime.

## Chapter 5: Environmental operation of diversion dams considering environmental flow (a multi- objective algorithm)

Full contents of this chapter have been published and copyrighted, as outlined below:

Sedighkia, M., Datta, B. and Abdoli, A., 2021. Minimizing physical habitat impacts at downstream of diversion dams by a multiobjective optimization of environmental flow regime. *Environmental Modelling & Software*, *140*, p.105029.

### 5.1 Introduction

Vital role of rivers as a main surface water resource to supply drinking, irrigation and industrial water demands has been identified from many years ago. Due to higher population and economic activities in future years, increasing offstream is expected which means instream flow would be reduced consequently (Postel, 1998). Given the serious concerns regarding damages to river ecosystems, concept of environmental flow regime has been defined that may guarantee sustainable ecological status of river (Tharme, 2003). In other words, environmental flow regime mainly protects aquatic habitats which could be assessed by different methods including historic flow methods, hydraulic rating methods and habitat methods (Jowett, 1997). Habitat approach as the best practice in assessment of environmental flow includes many methods such as instream flow incremental methodology (IFIM) and building block methodology (BBM) (Payne and Jowett, 2013; King et.al, 2000). IFIM is a qualified process to manage environmental impacts of water resources projects in which physical habitat simulation is an important factor. In fact, physical habitat simulation has been introduced as reliable tool to assess river habitats and environmental flow (Stalnaker, 1994).

Using diversion dams is prevalent to divert flow toward urban and agricultural lands. It is specifically very applicable for rivers in which construction of large dams is not possible due to technical or economic limitations. Thus, many diversion dams have been constructed all around the world. Purpose of these structures is to supply regional water demands mainly in close areas. Hence, a serious conflict between stakeholders and environmental managers would be anticipated. Stakeholders such as farmers are intended to receive maximum water. However, environmental requirements may be violated.

Therefore, there is a challenge how to allocate environmental flow at downstream of diversion dams. It is more important in arid and semi-arid regions where water scarcity is a limitation factor for agriculture. Thus, it is required to design an optimal environmental flow regime that is able to cover water demand and environmental requirements as much as possible. Environmental assessment methods do not sadly include any optimization component to design an applicable environmental flow regime.

Physical habitat simulation originally developed by applying univariate method to assess physical habitat suitability in a river. This method has been called univariate. It separately assesses suitability of physical factors without considering combined ecological effects. In other words, it uses mathematical model to combine suitability of physical parameters. In contrast, each method that is able to consider combined ecological effects could be considered as multivariate physical habitat assessment method. In other word, univariate method develops depth, velocity and substrate suitability separately. In the following, combined habitat suitability would be computed using three methods including product, minimum and geometric mean (Waddle, 2001). Univariate method has however been criticized in the literature due to lack of sufficient robustness to predict suitability of physical habitat such as spawning habitats (Noack et.al, 2013). Fuzzy multivariate method is another known approach to simulate physical habitats in the rivers that has successfully been utilized in some cases (e.g Mouton et.al, 2007; Jorde et.al, 2001; Marsili-Libelli et.al, 2013). Main limitation on its application is to develop physical habitat fuzzy rules. It is essential to have remarkable expert's knowledge for development of correct habitat fuzzy rules. However, it is not possible in many cases due to lack of ecological knowledge on many fish species. It seems that development of habitat suitability criteria must be based on actual observations and considering main physical factors such as depth and velocity simultaneously. Hence, data driven models are perfect tools to develop a robust physical habitat model.

New computers with high computational powers were a revolution to carry out complex computations in many branches of engineering. Data-driven models such as artificial neural networks (ANNs) or fuzzy inference systems (FISs) have been used in river and environmental engineering (Lobbrecht et.al, 2002). For example, these models have been utilized to optimize reservoir operation or runoff forecasting (e.g Chandramouli and Deka, 2005; Zhang et.al, 2018; Chang and Chang, 2006; Nourani et.al, 2009). ANNs and FISs suffer from some inherent deficits that have been addressed in the literature (Dumitru and Maria, 2013; Atmaca et.al, 2001). Hence, neuro fuzzy inference systems (NFISs) improved them by putting neural network in a fuzzy inference system. Adaptive neuro fuzzy inference system (ANFIS) is one of the applicable and known combined networks that has successfully been used for prediction of non-observed data (Jang, 1993). Data-driven models have been applied in different problems of water science. For example, Najafzadeh and Tafarojnoruz, 2016 applied neuro-fuzzy-based group method of data handling to evaluate the longitudinal dispersion coefficient in rivers. Their model was improved through particle swarm optimization. Results demonstrated that proposed model is robust to predict longitudinal dispersion coefficient. Moreover, Najafzadeh et.al, 2017 used data-driven model to predict local scour depth downstream of sluice gates. Results showed more reliability compared with conventional equations. Another example of applying data driven models in water science is prediction of riprap stone size (Najafzadeh et.al, 2018). Data-driven models have rarely been addressed as physical habitat model in the literature (e.g Im et.al, 2018; Jung and Choi, 2015; Zhao et.al, 2013). Previous studies used hybrid algorithm for training model.

Either practical protection of river habitats or environmental flow assessment needs a reliable optimization framework that should be able to present optimal daily or monthly environmental flow. In other words, an optimal environmental flow must not only maximize environmental benefits but it must be also able to maximize water demand benefits for stakeholders. In fact, it must be able to provide a counterbalance between environmental requirements and water demands. Hence, a multiobjective optimization model is a requirement for designing environmental flow regime. Multiobjective optimization is relatively known method to solve optimization problems that has been addressed for different problems such as reservoir operation (Guo et.al, 2013; Si et.al, 2019). We focused on using multi objective particle swarm optimization (MOPSO) in the present chapter. Hence, it is essential to review some previous studies regarding using this algorithm. Hu et.al, 2020 used MOPSO for feature selection by fuzzy cost. Moreover, Zhang et.al, 2012 developed a bare-bones multi-objective particle swarm optimization algorithm for environmental/economic dispatch. MOPSO has been utilized for building energy performance successfully (Yong et.al, 2020). Zhang et.al, 2018 developed a decomposition-based archiving approach for multi-objective evolutionary optimization. Different applications of MOPSO in the literature demonstrate its robustness for engineering problems.

The Present chapter proposes a coupled PSO-ANFIS based physical habitat model and multiobjective optimization model to optimize environmental flow. In the first step, we developed PSO-ANFIS based habitat model to simulate physical habitats. In the second step, habitat hydraulic function has been developed using linked ANFIS habitat model- 2D hydrodynamic model. In the third step, an irrigation demand function was developed. Then, a multi objective optimization model has been implemented to maximize two objective functions. Finally, analysis on results of optimal environmental flow was carried out. The main novelty of present chapter is development of a new framework to assess environmental flow at downstream of diversion dams in which three components have been coupled to improve assessment of environmental flow including ANFIS based physical habitat model, benefit function of farming and a multiobjective evolutionary algorithm. In other words, proposed framework opens a new window to assess environmental flow by a complex optimization process. It should be noted that proposed physical habitat based methods to assess environmental flow in the previous studies have a significant drawback which is lack of optimization framework in the structure of method. Present chapter covers this drawback by presenting a novel framework. Proposed method could be considered as powerful tool to optimize environmental flow regime at the downstream of diversion dams.

## 5.2 Application and methodology

### 5.2.1 Study area and field observations

The Proposed method has been utilized in the Tajan river basin as one of the most important rivers in southern Caspian Sea basin. This river is responsible for supply of irrigation demand in the region. A diversion dam has been constructed in the Sary city where is accountable for water supply of vast farms in this area. Main crop in this river basin is rice which means this crop could be considered as representative crop for assessment of agricultural water demand. Figure 5-1 displays location of Tajan river basin. Populated irrigated farms could be seen at downstream of Sari diversion dam. Owing to importance of downstream habitats, protection of these aquatic habitats is essential as well as supply of irrigation water demand. In other words, Optimizing of water demand for agriculture and environment is necessary.

Based initial ecological studies, Capoeta capoeta was selected as target species. More detail on this species has been addressed in the literature (Kiabi et.al, 1999; Abdoli et.al, 2008). We selected adult life stage in this study because a remarkable population of this life stage was observed at downstream river reach. Moreover, we carried out sampling process in different seasons for better assessment of average suitability. Fish observation and measurement of depth and velocity in microhabitats were required field studies. Sampling methods classified in two groups including direct and indirect methods. Each method might have its own strength and drawbacks (Harby et.al, 2004). For example, video telemetry is a direct method for observing fish in actual fish habitats. However, it is not useable in turbid waters. In contrast, electrofishing is an applicable indirect method for sampling. We applied electrofishing due to previous experience on its application and its advantages. We utilized minimum voltage to reduce environmental impacts. Velocity has been measured using propeller as well as depth using large metal ruler (Harby et.al, 2004).

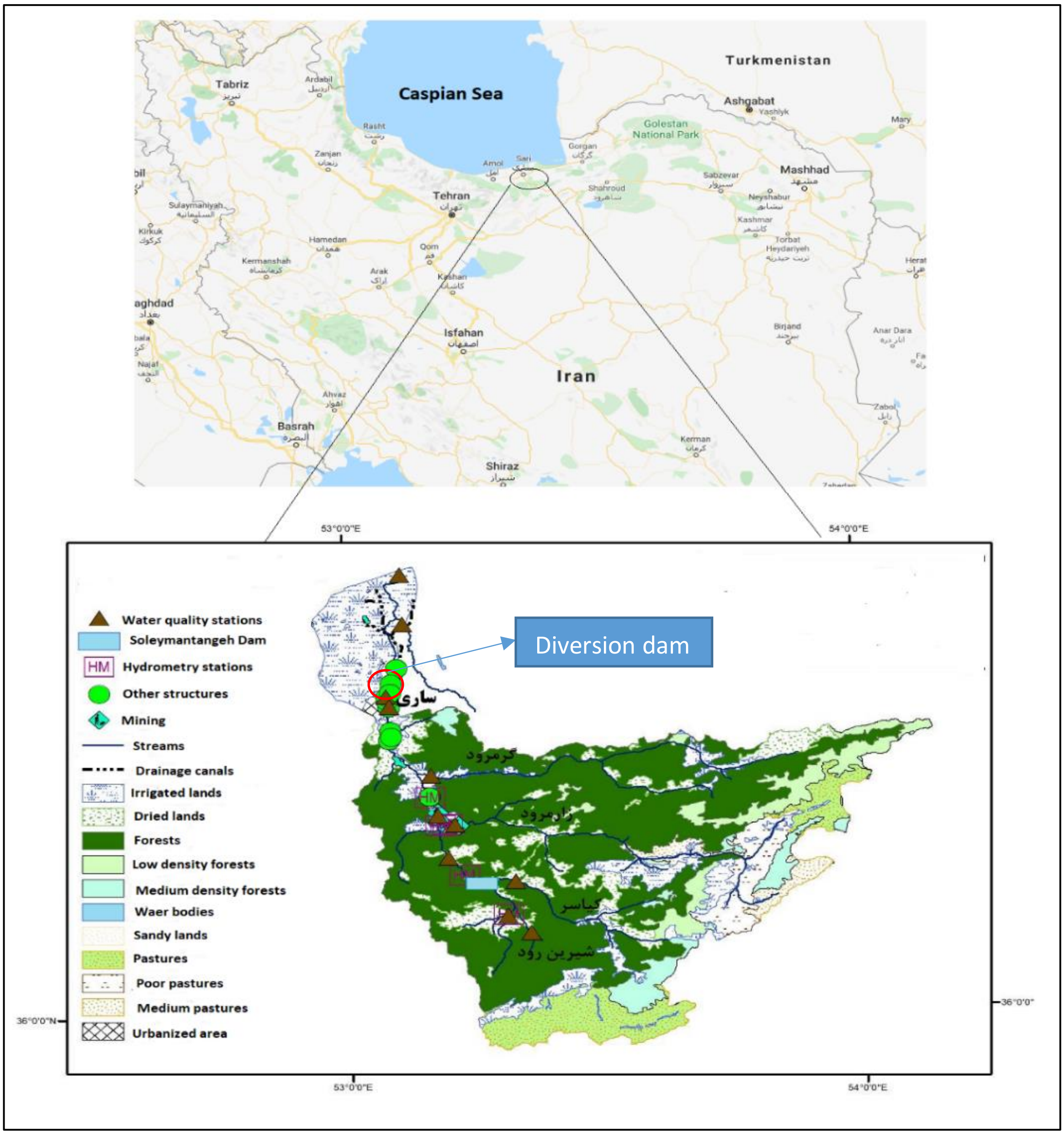



**Figure 5-1- Land use and river network map of Tajan basin**

### 5.2.2 Architecture of data-driven physical habitat model

Three main physical factors may usually be taken into account to simulate physical habitats including depth, velocity and substrate (Sedighkia et.al, 2017). However, we only considered depth and velocity due to some technical considerations. First, bed particle size in representative reach was relatively similar in different parts that means effect of substrate on habitat suitability was not probable. Moreover, our observations in other parts of river indicated that physical habitat suitability for target species is mainly depended on depth and velocity as key hydraulic characteristics. Hence, data-driven physical habitat model was finalized based on depth and velocity. Main features of developed network has been displayed in Table 1. Moreover, we used particle swarm optimization (PSO) which is a robust evolutionary algorithm to train ANFIS based habitat model (Kennedy and Eberhart, 1995). PSO-ANIFS flowchart is shown in the figure 5-2. It should be noted that 80% of sampled data was used to train data-driven model which means 20% of data was utilized to test and verify habitat model. In fact, 200 points were measured in different parts of river to develop physical habitat model. 160 points was used for training and 40 was used for testing. Nash–Sutcliffe model efficiency coefficient (NSE) and root mean square error (RMSE) were utilized to measure performance of data-driven model. NSE=1 means model is perfect regarding predictive skill. However, NSE more than 0.5 demonstrates acceptable predictive skills for the model (McCuen et.al, 2006). Equation 1 displays mathematical definition of this index in the present chapter. NSE is a robust index to measure predictive skills of model that might be utilized in different simulation processes such as physical habitat simulation. However, it is initially developed for hydrological modelling.

$$NSE = 1 - \frac{\sum_{i=1}^{T} |M_i - O_i|}{\sum_{i=1}^{T} |M_i - O_m|} \tag{1}$$

where M is modelled habitat suitability an O is observed or recorded habitat suitability. Equation 2 displays mathematical definition for RMSE

$$RMSE = \sqrt{\frac{\sum_{i=1}^{T} (M_i - O_i)^2}{T}} \tag{2}$$

**Table 5-1- Main characteristics of developed ANFIS based habitat model**

| **Inputs** | **Number of MFs (inputs)** | **Type of MFs (inputs)** | **Outputs** | **Number of MFs (Output)** | **Type of MFs (Output)** |
|---|---|---|---|---|---|
| **Depth** | 10 | Gaussian | Habitat suitability Index (between zero and one) | 10 | Linear |
| **Velocity** | 10 | Gaussian | | | |

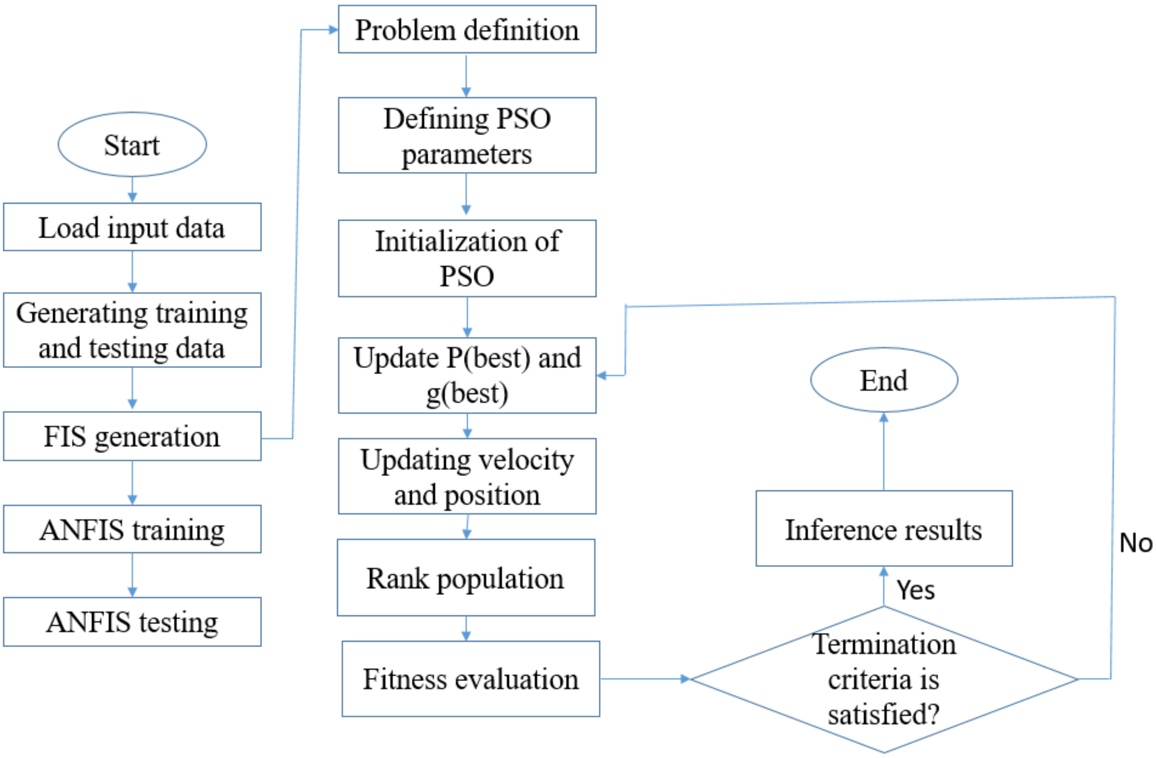



**Figure 5-2-PSO-ANFIS flowchart**

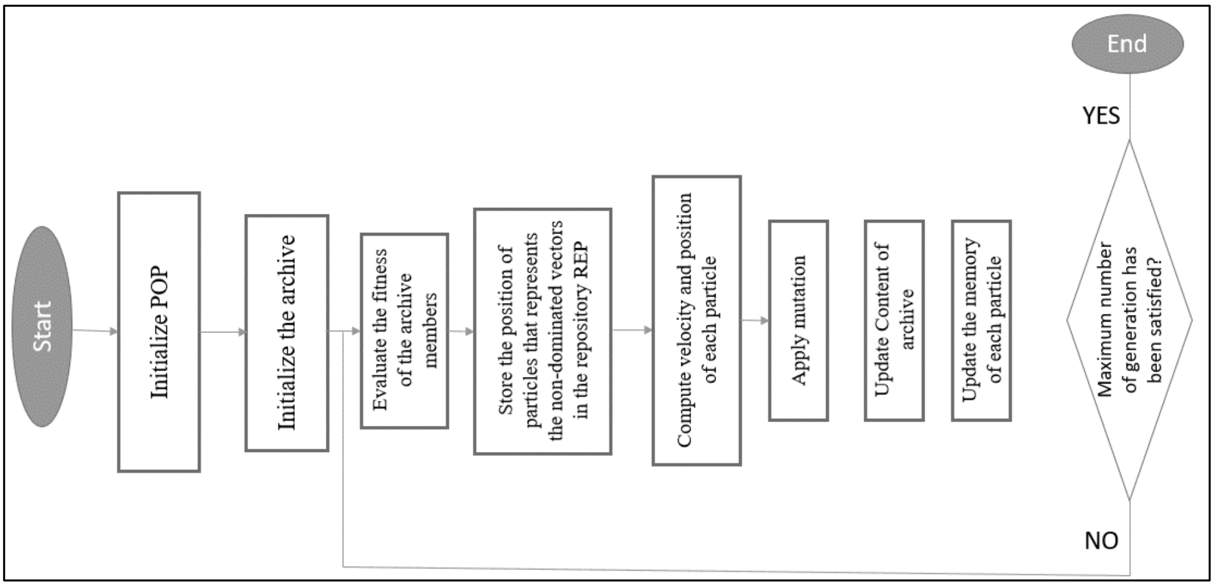



**Figure 5-3-Mutilobjective Particle swarm optimization (MOPSO) flowchart (Coello et.al, 2004)**

### 5.2.3 Habitat hydraulic model

Coupled PSO-ANFIS habitat model-2D hydraulic model is able to simulate physical habitat suitability. We selected a representative reach to simulate physical habitat. Then, digital elevation model (DEM) of main channel and flood plain was provided by data bank of department of environment. Finally, two-dimensional hydraulic modelling was carried out using HEC-RAS 2D which is a known model to simulate depth and velocity in rivers (Brunner, 2016). Recent studies corroborated efficiency of HEC-RAS 2D to simulate habitat hydraulics. More detail on its method and application for habitat hydraulic modelling is available in the literature (Papaioannou et.al, 2020). Moreover, we used weighted useable area concept to assess suitability of physical habitat as displayed in Equation 3

$$WUA = \left(\frac{\sum_{i=1}^{i=N} HSI_i.A_i}{L}\right).1000 \tag{3}$$

where A is area of each habitat cell, L is total length of reach and HSI is habitat suitability index in each cell. Equation 3 computes WUA in each 1000 metres of river reach, which is properly able to demonstrate physical habitat suitability. HSI is outcome of combining simulated depth and velocity with ANFIS based habitat model. In other words, ANFIS based habitat model computes suitability by considering simulated depth and velocity in each cell. Based on results of habitat suitability for all of the cells, weighted useable area is computed by equation 3 for simulated river reach.

An important point should be noted regarding 2D hydraulic modelling. Calibration of 2D models is usually difficult. In the present chapter, extensive field studies were helpful to calibrate 2D hydraulic model. In other words, depth and velocity were measured in different cross sections of the simulated river reach. We measured depth and velocity along different cross sections by propeller and large metal ruler. Moreover, flowrate was measured by sub-division methods. It should be noted that this study was part of a comprehensive project in this river basin. Thus, measurements were carried out in several days in a year that provided an appropriate data bank of depth and velocity in different cross sections. In other words, depth and velocity distributions were provided in different flows. Then, collected data was utilized to calibrate 2D hydraulic model by comparing results of model with the observed depths and velocities in each cross section and revising calibration parameters such as Manning coefficient.

### 5.2.4 Optimization model

Multi objective optimization by particle swarm optimization method (MOPSO) has been used in many previous studies for hydro-environment systems (Reddy and Kumar, 2007; Niu et.al, 2018). Hence, extensive description on its method has been addressed in the literature. Figure 5-3 displays MOPSO flowchart that has been utilized in the present framework (Coello et.al, 2004). Two objective functions were defined. First function was defined to maximize normalized weighted useable area. Moreover, second function was defined to maximize irrigation demand or benefits from the rice fields as the main crop in the river basin. Used objective functions have been displayed in Equations 4 to 6.

$$z1 = \sum_{t=1}^{T} NWUA_t = \sum_{t=1}^{T} f(QE_t) \tag{4}$$

$$z2 = \sum_{t=1}^{T} NB_t = \sum_{t=1}^{T} g((QT_t - QE_t) \tag{5}$$

$$z = [z1\ z2] \tag{6}$$

where NWUA is normalized weighted useable area that is between zero and one, QE is environmental flow, QT is total available flow in the river, NB is normalized benefit from current agricultural activities with focus on the rice fields. As a more description on optimization model, it has two objectives. The first objective is to maximize protection from downstream habitats. The second objective is to maximize benefits for the farms. For the first objective, it is required to maximize normalized weighted useable area function. Flow rate of maximum possible NWUA was defined as ideal environmental flow for further analysis. On the other hand, normalized benefit function was defined based on maximum requested water demand for the rice farms. In fact, main limitation for agriculture in the study area was lack of sufficient water. NB=100% means maximum requested water demand is supplied. In contrast, NB=0 means no water is available for farms. It was essential to use some indices to measure system performance of environmental flow optimization model. As presented, ideal environmental flow provides the highest physical habitat suitability. In other words, physical habitat impacts are close to zero. Two indices were developed which has been called reliability and vulnerability indices as displayed in equations 7 and 8.

$$\alpha_E = \frac{\sum_{t=1}^{T} AE_t}{\sum_{t=1}^{T} IE_t} \tag{7}$$

$$\gamma_E = Max_{t=1}^{T}\left(\frac{IE_t - AE_t}{IE_t}\right) \tag{8}$$

where AE is actual environmental flow and IE is ideal environmental flow. It should be noted IE means environmental flow in which WUA is maximum. In fact, it is peak point of WUA curve. These indices have originally been developed to measure system performance of reservoir operation optimization models (e.g Ehteram et.al, 2018). Figure 5-4 displays how we utilized MOPSO to optimize environmental flow in the present chapter. Two constraints were considered in the optimization system including upper limit and lower limit for environmental flow. Upper limit is natural flow in the simulated period and lower limit is minimum environmental flow.

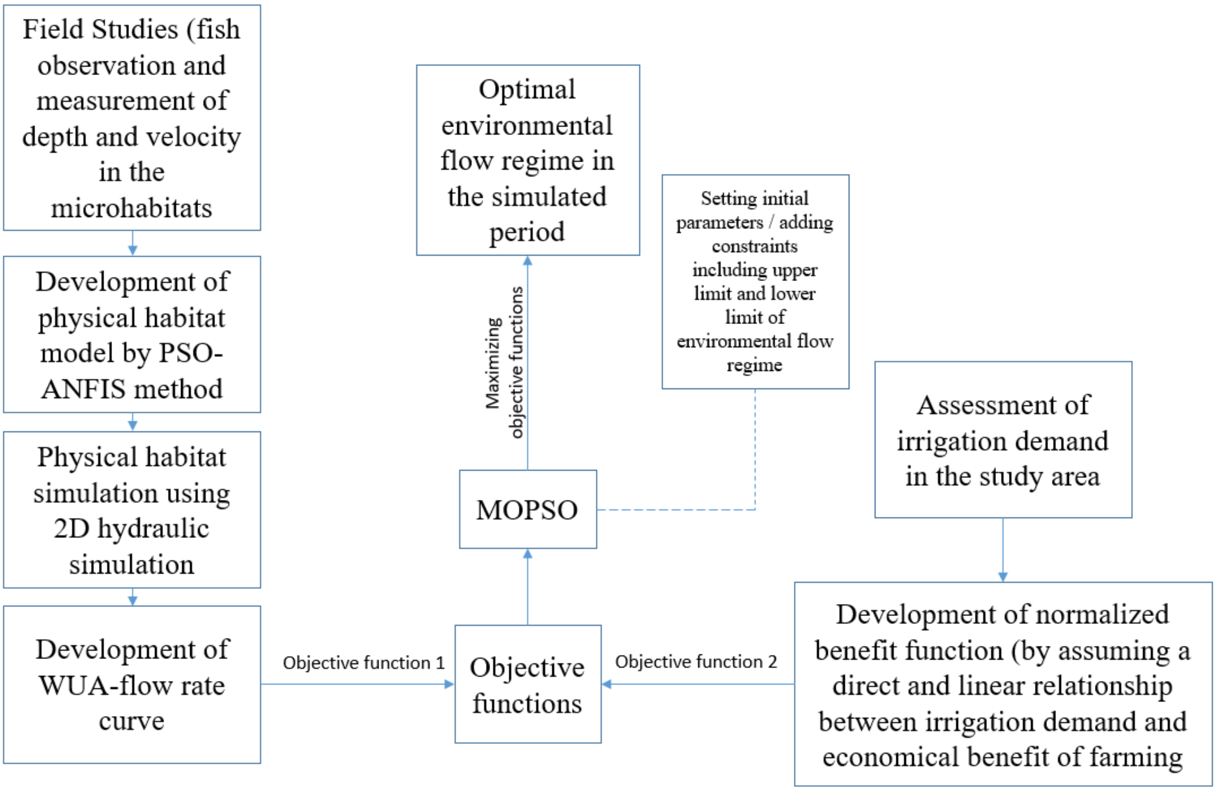



**Figure 5-4- Workflow of optimization model in the present framework**

## 5.3 Results and Discussion

Figure 5-5 displays depth and velocity distribution of sampled microhabitats which has been utilized in the testing process of physical habitat model. It seems that provided data bank for testing process of habitat model is sufficient. It covers a wide range of microhabitats. Depth range is between 0.2 and 1.4 m as well as velocity, which is between 0.3 and 1.2 m/s. In other words, diversity of microhabitats in terms of depth and velocity demonstrated that results of testing is reliable and data-driven habitat model could be used for further applications. Figure 5-6 displays habitat suitability by PSO-ANFIS habitat model and recorded microhabitats. It demonstrates that model is robust to simulate physical habitats. Based on computations, NSE is 0.93, which corroborates robustness of physical habitat model. Moreover, RMSE is 0.009, which indicates high accuracy of physical habitat model. Hence, proposed PSO-ANFIS model could be utilized for the optimization model.

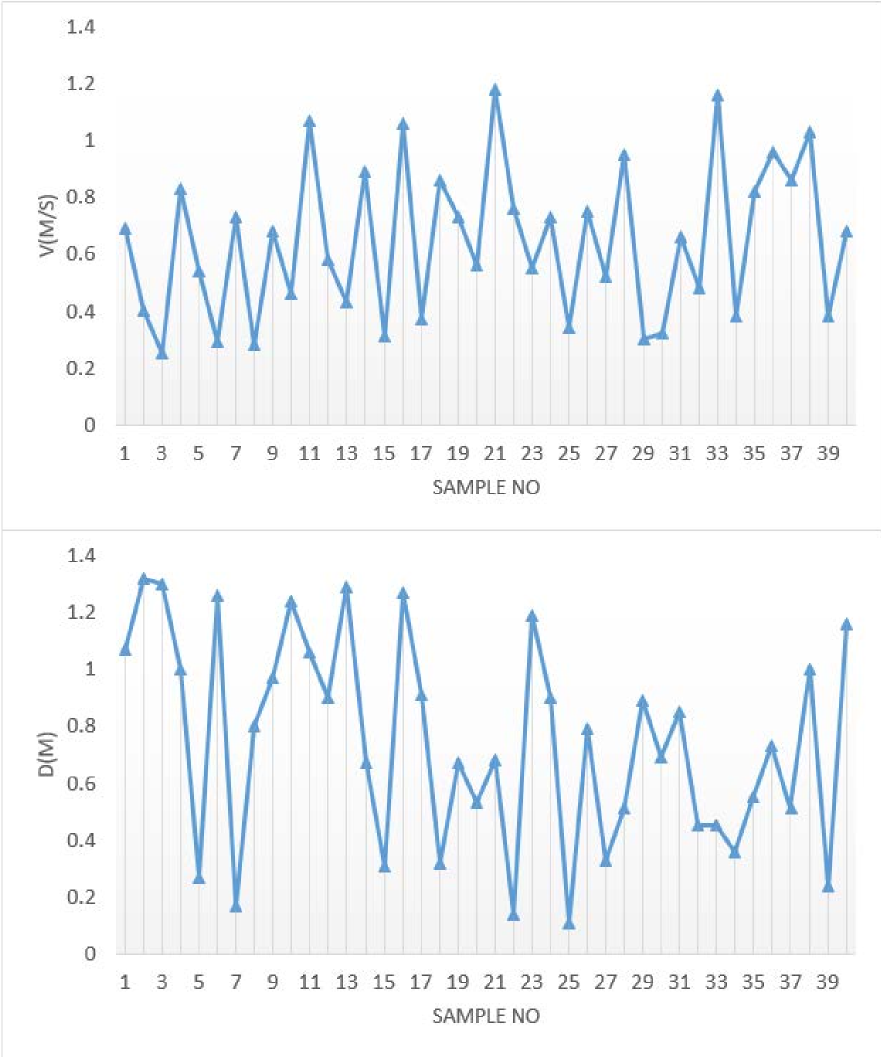



**Figure 5-5-Depth and velocity distribution of recorded microhabitats**

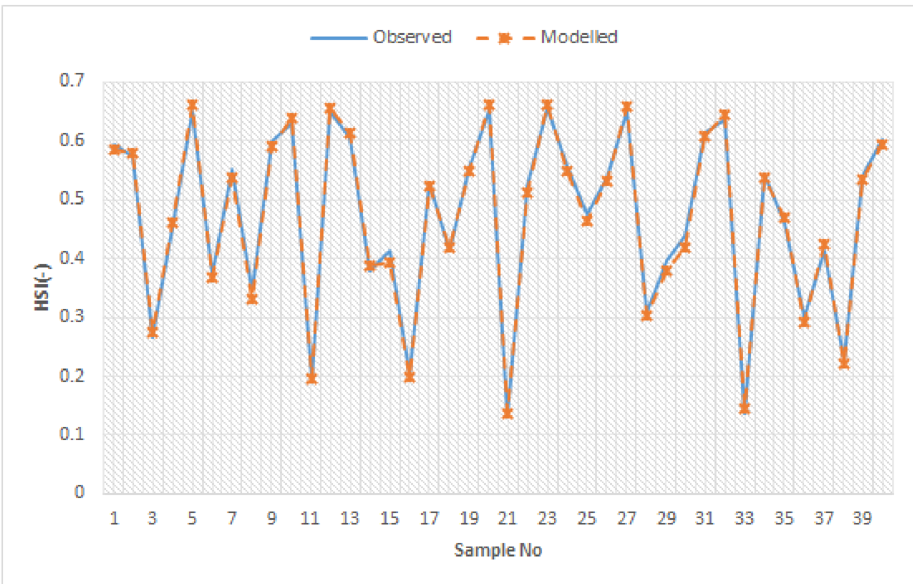



**Figure 5-6-Observed and modelled habitat suitability of testing process**

In the next step, presenting results of habitat hydraulic simulation is necessary. Figure 5-7 and 5-8 display depth and velocity distribution respectively in some simulated flows. Alteration of depth and width of river reach could be observed by changing flow. In the lowest simulated flow, depth would be less than 1.65 m, whereas increasing depth could be observed to 2.21 m, which means increase in depth might not be very remarkable due to geometric characteristics of simulated reach. It should however be noted that this change is considerable for habitats. In other words, it can dramatically affect physical habitat suitability of stream. Figure 5-9 has displayed habitat suitability maps. It demonstrates that incrementing rate of flow may increase total available habitat area. However, some habitats are unsuitable especially close to centreline of streams. Increasing of velocity significantly affect habitat suitability. Hence, by increasing discharge, suitable habitats mainly are located near to stream banks. Interestingly, low discharges such as 1 cumecs and 5 cumecs provide suitable habitats for target species. High flow rates including 21, 25 and 30 cumecs are not appropriate for target species. However, it should be noted that these flows are probable during flood seasons. Furthermore, Figure 5-10 shows developed NWUA function. Equation 9 displays conditional form of NWUA that has directly been used in the programming of optimization model. Based on available agricultural data, hydro module irrigation was calculated. In Equation 10 where x is continuous discharge.

```
for i=1:365                                                          (9)
   if (x(i)<1)
       WUA=(0.639998*x(i))+0;
   else if (1<=x(i))&&(x(i)<5)
            WUA=(0.09*x(i))+0.5499;
    else if (5<=x(i))&&(x(i)<8)
            WUA=(-0.00727*x(i))+1.036355;
    else if (8<=x(i))&&(x(i)<12)
            WUA=(-0.01048*x(i))+1.062002;
    else if (12<=x(i))&&(x(i)<17)
            WUA=(-0.01168*x(i))+1.076473;
    else if (17<=x(i))&&(x(i)<21)
            WUA=(-0.01799*x(i))+1.183648;
    else if (21<=x(i))&&(x(i)<25)
            WUA=(-0.01008*x(i))+1.017579;
       else
            WUA=(-0.00613*x(i))+0.918955;
        end
        end
        end
        end
```

```
          end
        end
WUAF=WUAF+WUA;
        z1=WUAF;

    end
```

$$NB = (-0.0083(X^2)) + (0.1818X) + 0.0015 \tag{10}$$

Figure 11 displays non-dominated solutions for used objective functions. The best solution provides minimum distance between NWUA and NB at Z= [0.7387 0.5722]. Figure 5-12 as direct output of optimization model shows daily environmental flow proposed by multiobjective optimization model. Unit of flow is cubic meters per second (cms) or $m^3/s$. Furthermore, available flow and supplied water demand are shown in this figure. It should be noted that a minimum environmental flow has been considered in development of optimization model which provides minimum required protection from the habitats in all of the time steps. This flow was considered 0.7 cms approximately. This value was defined based on opinion by an experienced ecologist. In fact, minimum required physical habitat suitability was defined 45% that is equal to 0.7 cms.

Management of environmental flow and agricultural water demand are practically monthly. Thus, it is essential to convert daily flow to monthly flow to measure performance of optimization model. Figure 5-13 displays monthly optimal environmental flow regime, total available flow and optimal water demand respectively. Results demonstrate that MOPSO is able to propose an optimal regime for environmental flow and water demand. Measurement of system performance demonstrated half of ideal environmental flow could be supplied for river habitats. It sounds that proposed method is reliable to assess environmental flow. Supply of ideal environmental flow is not naturally possible due to natural changes of river flow. Supply of half of ideal annual environmental flow demonstrates that developed model is reliable for further studies. Moreover, vulnerability index indicates maximum deviation from ideal environmental flow is 55%.

In the next step, it is essential to compare results of this research work with the previous assessments in the case study. Tennant ,1976 developed a method to assess environmental flow based on environmental observations in some rivers of the United states. Tennant is one the oldest methods proposed for assessing environmental flows. Newer methods have been developed in the recent decades such as physical habitat simulation and building block methodology. However, newer methods are not officially in use due to complexities to use these methods in practical projects and lack of enough experts for these methods in many developing countries such as Iran. Tennant method is accepted method by Iranian ministry of energy and previous environmental flow studies have been carried out by this method. We used this method for comparing current used method in this river basin with proposed advanced method. Moreover, Tennant method provides appropriate initial estimation on environmental flow.

Tennant's recommendations are based on assessing environmental flow as a proportion of mean annual flow in different months. Different statuses were considered including poor, good and outstanding based on Tennant method. Poor status means least protection of river habitat. Outstanding status means offstream flow is minimized and protection is maximized in the river. Comparison is helpful to compare proposed ecological status by optimal environmental flow with the natural river flow regime. Figure 5-14 displays monthly proposed environmental flow compared with Tennant method. Optimization model proposed environmental flow regime much more than poor status that means assessed environmental flow is reliable. Moreover, it is much lower than outstanding status in some months that means it is able to consider required water demand properly. In other words, environmental flow has not been overestimated. Assessed environmental flow is close to good status especially in April- September. Environmental flow by Tennant for outstanding and good statuses have considerably reduced in some months. Hence, optimal environmental flow is closer to outstanding ecological river status. Figures 5-15 and 5-16 display annual environmental flow by proposed optimization method and different statuses by Tennant method. It demonstrates that proposed method provides environmental flow equal to good or outstanding ecological status.

Average NWUA is 0.7 that means proposed multi-objective optimization model is able to protect physical habitats properly. In fact, it is able to provide 70% of maximum. It seems that proposed method provides proper ecological status for the river ecosystem. River might have unsuitable habitats in natural flow. Thus, performance of optimization model is acceptable. Maximum requested water demand is 208 MCM and supplied demand by the proposed optimization system is 125 MCM. It demonstrates that optimization model is able to protect 60% of economic profits. In other words, more than half of agricultural water demand has been supplied. It should be noted that a direct and linear relationship between irrigation demand and economic profit was assumed in the present chapter. Optimization model provides a balance between environmental requirements and water demands. Using proposed method is recommendable to assess environmental flow regime. The most important advantage of proposed method is to enhance reliability of environmental flow assessment method by an optimization framework.

Some points must be discussed to clarify advantages of the proposed method. In other words, why the proposed strategy/mechanism can achieve good results? Considering a robust function for environmental requirement of the river ecosystem is one of the main reasons for robustness of proposed framework. In fact, physical habitat suitability is a clear definition on suitability of habitats in a stream. Hence, applying weighted useable area function in the structure of the optimization model demonstrates applicability of proposed method for the future studies. Moreover, proposed method is able to consider requirements for the environment and benefits for the farms simultaneously. Previous environmental flow assessment methods lack ability of optimizing instream flow. We assumed that scarcity of water is the main limitation in development of benefit function that is a correct assumption for many arid areas. Furthermore, using a robust multi-objective optimization method is another reason for achieving good results. Optimizing environmental flow in each time step might be complex that needs a robust optimization solution. Optimization algorithm was able to maximize objective functions in the simulated period well.

It is required to discuss on computational complexities of the proposed method to optimize environmental flow. As a general definition on computational complexities, it is the amount of resources required to run it with focus on time and memory requirements. Low computational time might be the most advantages for the proposed framework. Our experience demonstrates that it is efficient in terms of computational time in short-term simulation period. However, covering long-term simulation period might need considerable time. It seems that implementing more complex framework might increase computational time as a disadvantage. It should be noted that practical projects need numerous simulations. Hence, computational time must be noticed in the application of proposed framework. Moreover, performance of proposed optimization model is efficient in terms of memory requirement. To sum up, it seems that low computational complexity is an advantage for the proposed method.

Limitations of proposed method should be noted for the future studies. Field studies is one of the limitations for applying method. Required field studies might be expensive and time consuming. Moreover, we used a linear relationship between economic benefits and irrigation demand based on requirements of case study. However, it is not correct for all of the cases that is another limitation in the proposed framework. Furthermore, absence of considering requirements for water quality is another limitation for the proposed framework. It seems that these limitations must be considered in the future studies to improve optimization model. In other words, we recommend focusing on methods to reduce costs of field studies, considering water quality requirements and improving benefit function in the future studies. It should be noted that proposed method is based on environmental values of river ecosystem and water demand by agriculture. However, using this method in other application might need some improvements. For example, if diversion project is utilized for supply of urban water, it will be needed to add loss function of urban water supply to the optimization system. In fact, proposed method was defined based on two principal aspects for the river engineering projects including suitability of aquatic habitats at the downstream of diversion dam as environmental requirement and supply of irrigation demand in the study area. Using proposed framework for supply of urban water needs development of urban water loss function.

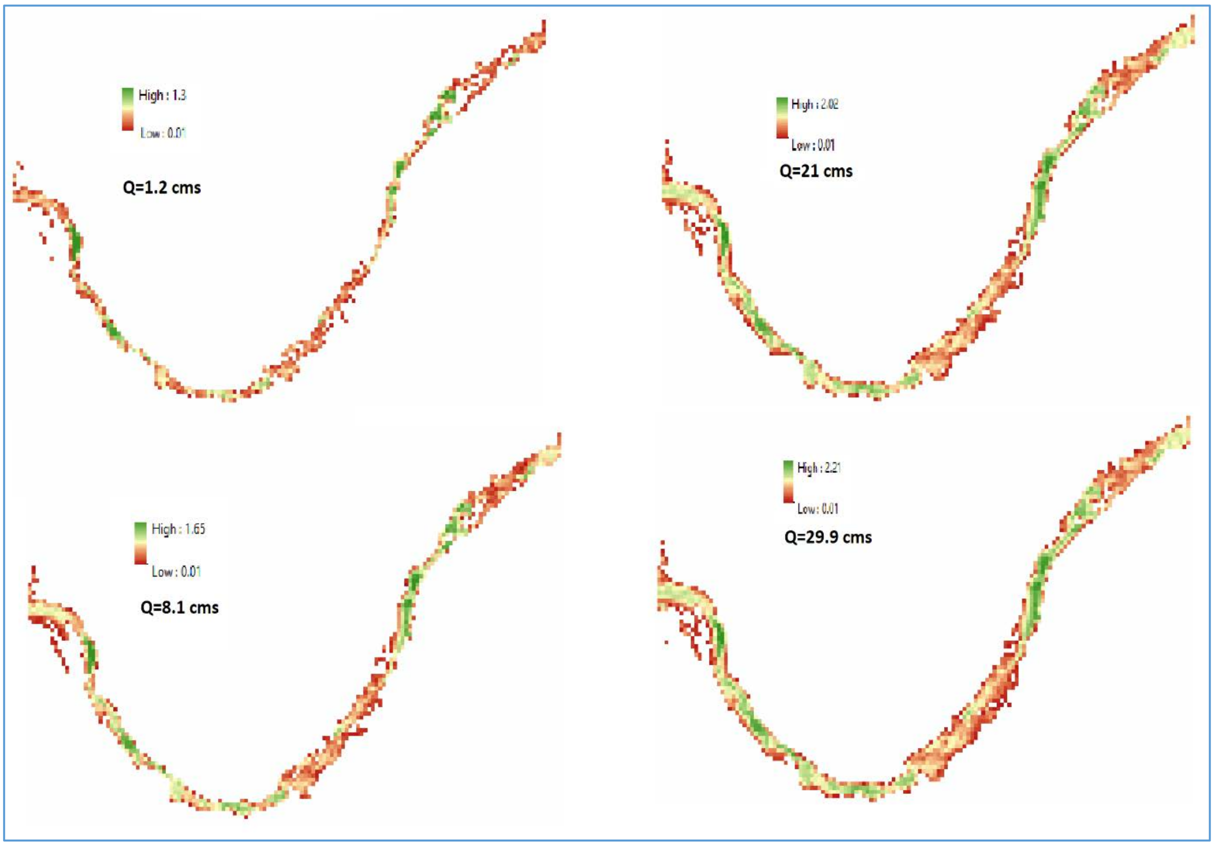



**Figure 5-7-Depth distribution map as a sample of two dimensional hydraulic simulation results**

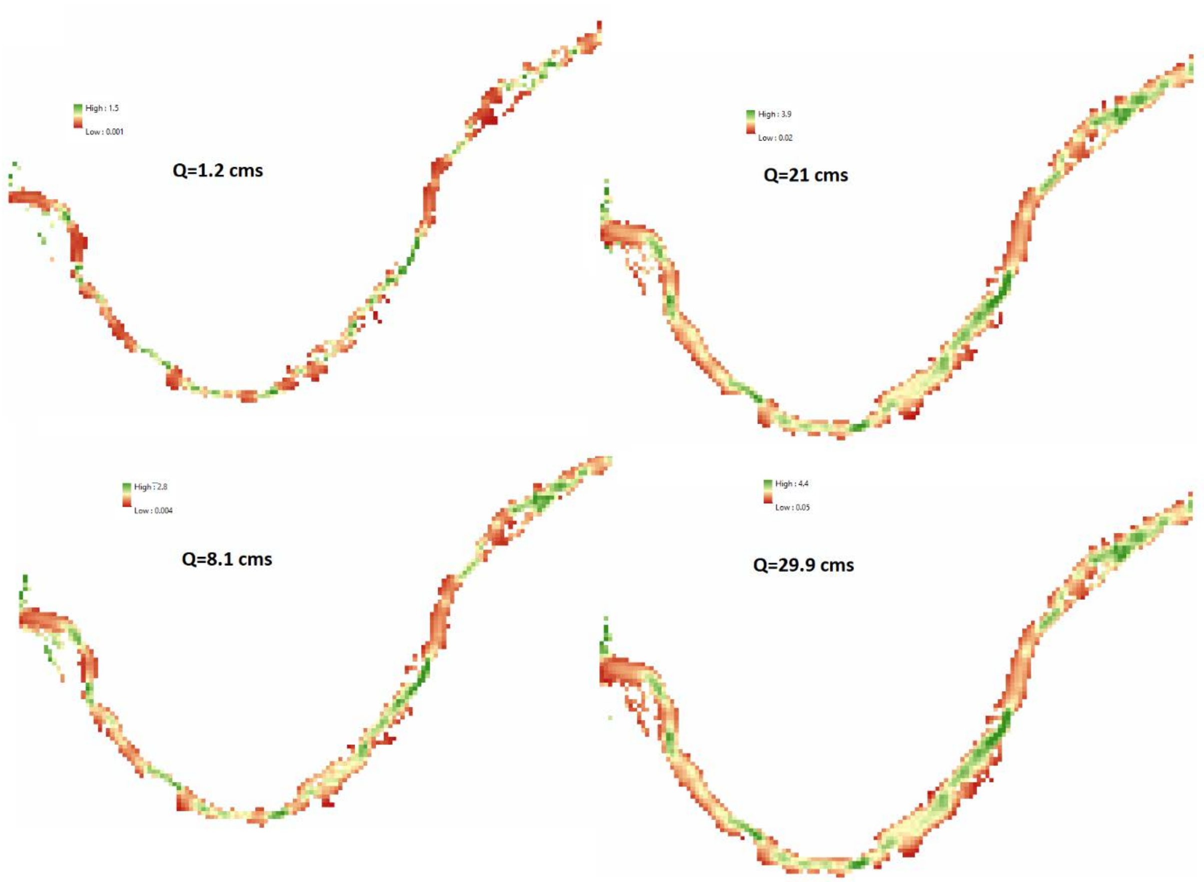


**Figure 5-8-Velocity distribution map as a sample of two dimensional hydraulic simulation results**

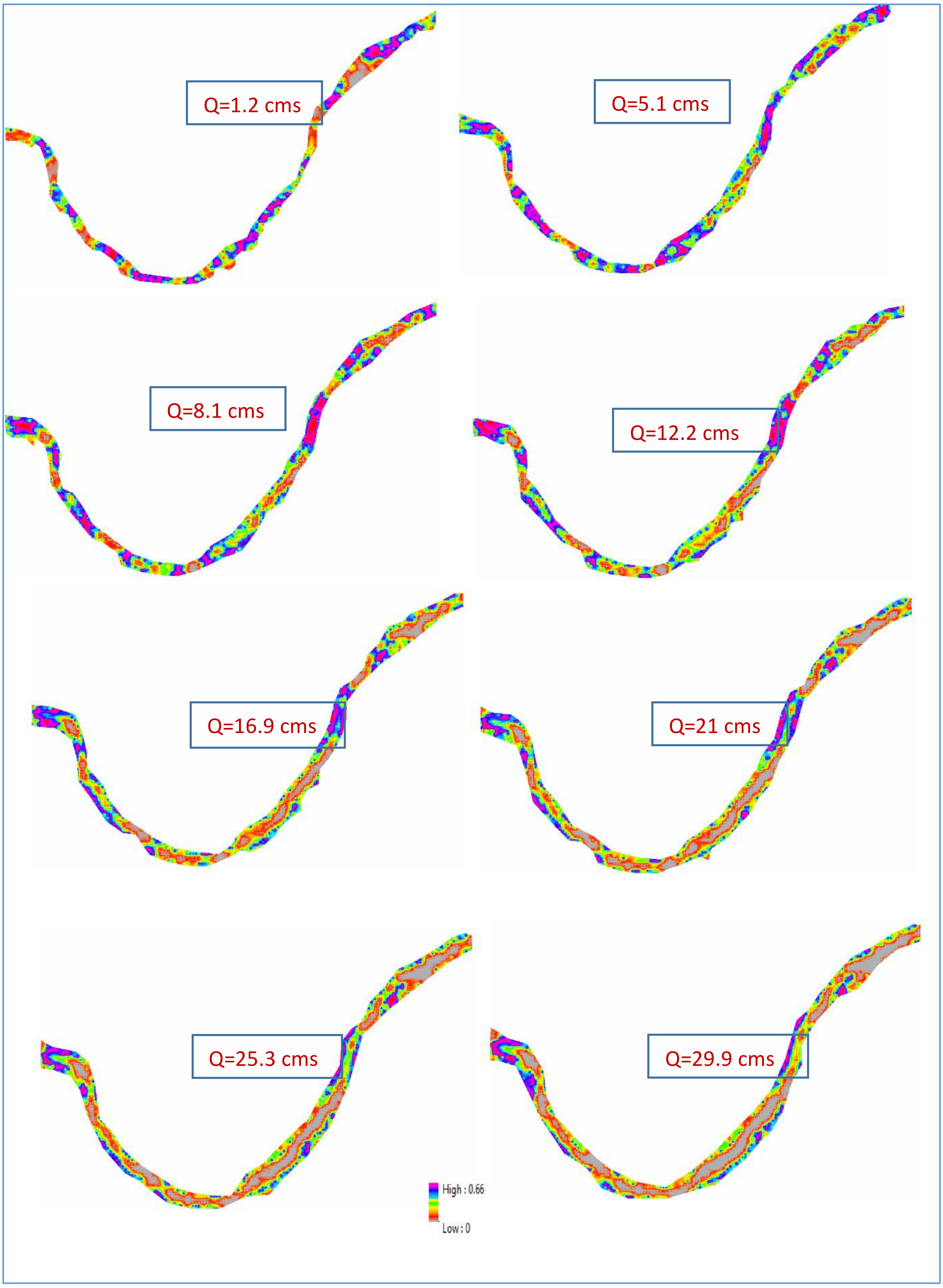


**Figure 5-9-Habitat suitability distribution maps**

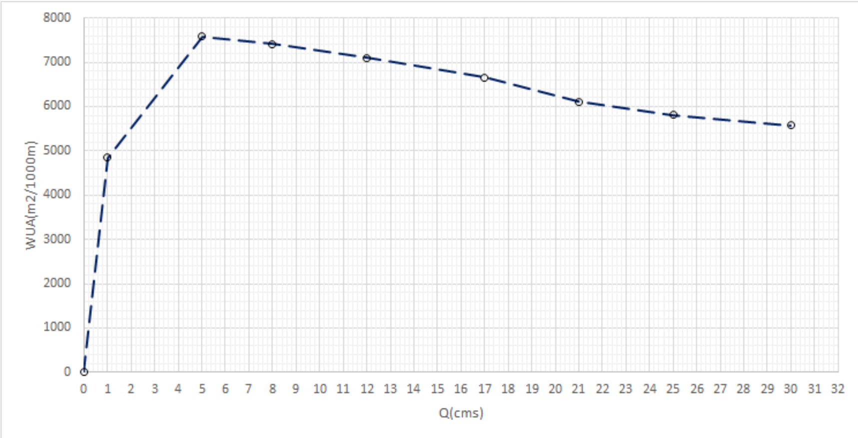



**Figure 5-10-WUA curve- final output of habitat hydraulic simulation**

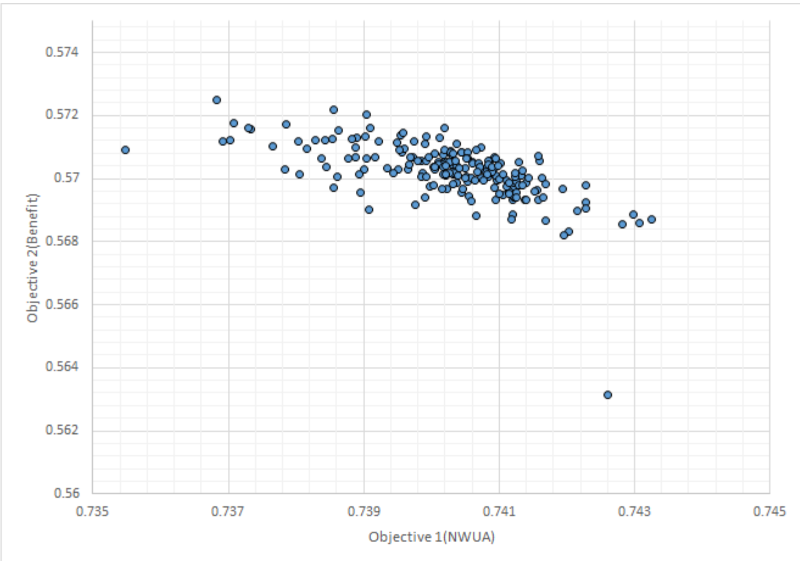



**Figure 5-11-Trade-off analysis for finding the best solution by MOPSO**

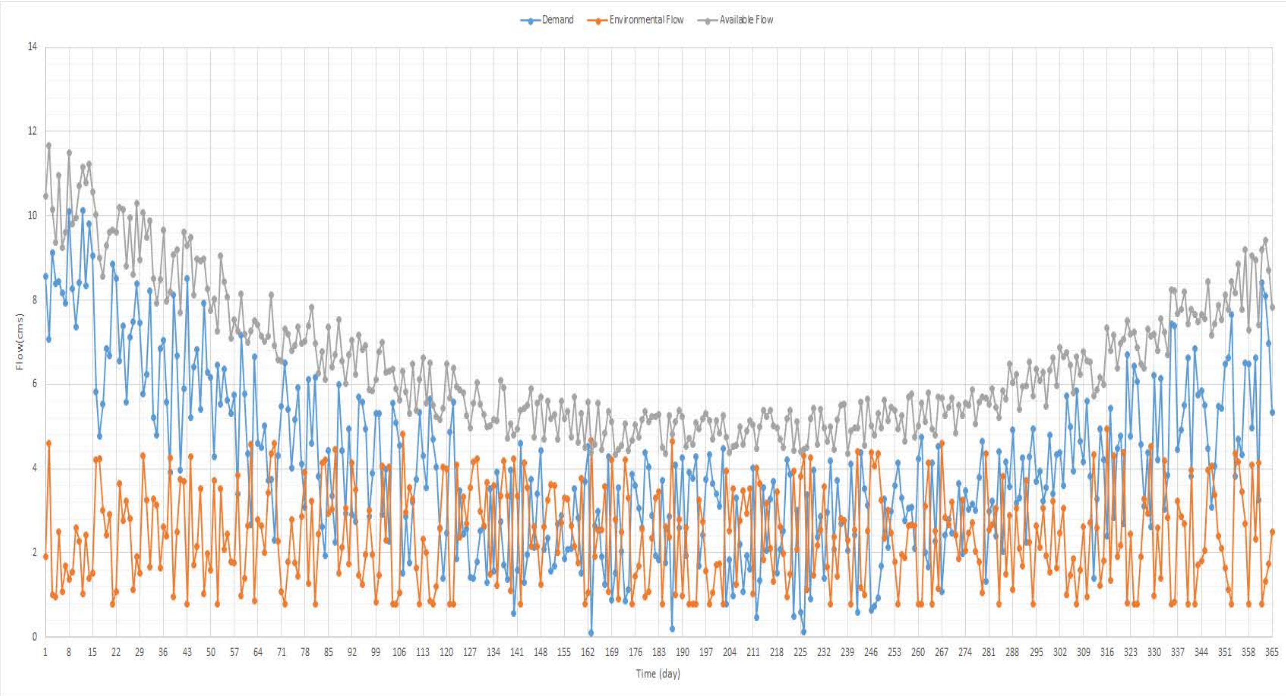



**Figure 5-12-Daily environmental flow as direct output of multi objective optimization**

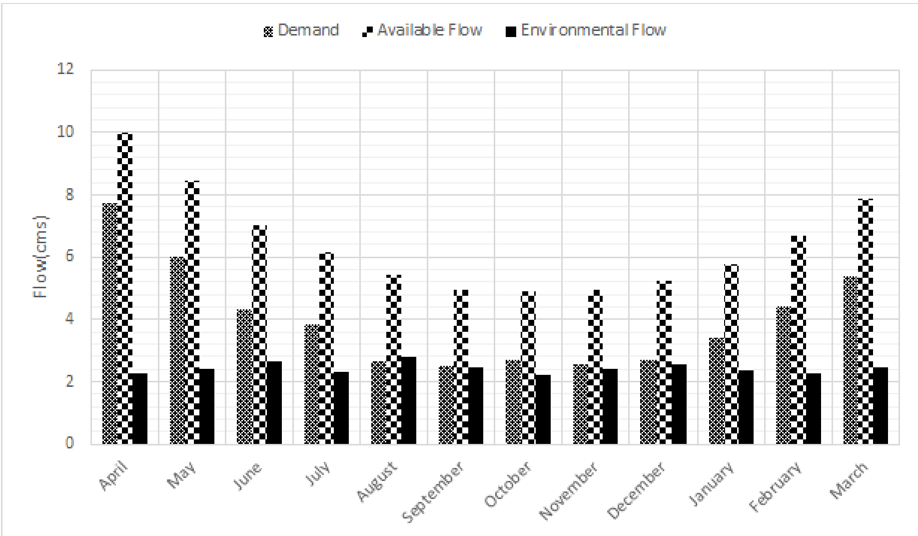



**Figure 5-13-Monthly environmental flow as optimized environmental flow regime for further applications**

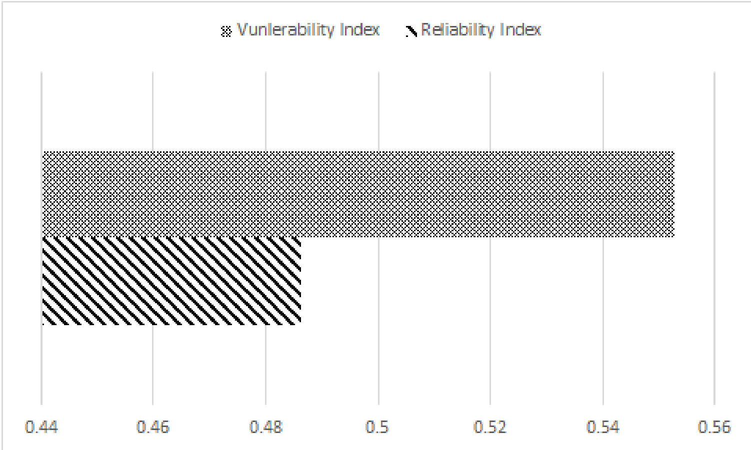



**Figure 5-14-Measurement of system performance indices**

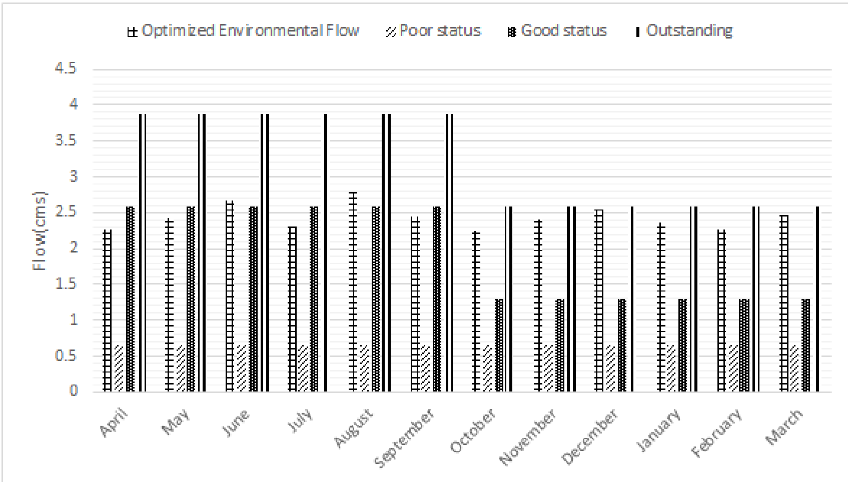



**Figure 5-15-Comparison of optimal environmental flow regime with Tennant method**

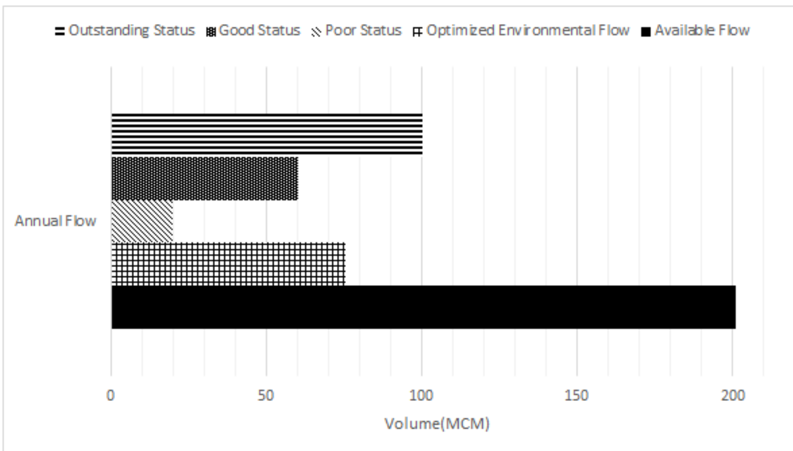



**Figure 5-16-Comparison of optimized annually environmental flow by general Tennant's recommendations**

## 5.4 Summary

This chapter links physical habitat simulation with the irrigation loss function to assess optimal environmental flow regime. The main motivation is Lack of optimization framework in the structure of reliable environmental flow methods such as physical habitat simulation. Data-driven model was used to simulate physical habitats. Moreover, a multi-objective particle swarm optimization was utilized to optimize environmental flow regime by considering two objective functions including weighted useable area function and normalized benefit function for irrigation demand. Based on results, physical habitat data-driven model was robust to assess habitat suitability. Moreover, proposed multi objective optimization model is able to assess environmental flow properly. In the case study, physical habitat impact was minimized to 30% that means 70% of useable habitats would be protected. In contrast, 60% of maximum requested water demand would be supplied which implies a fair balance between demand and environmental flow.

## Chapter 6: Incorporating potential climate change impact in environmental operation of diversion dams

Full contents of this chapter have been published and copyrighted, as outlined below:

Sedighkia, M. and Abdoli, A., 2022. Balancing environmental impacts and economic benefits of agriculture under the climate change through an integrated optimization system. International Journal of Energy and Environmental Engineering, pp.1-14.

### 6.1 Introduction

Energy and water are the key components in the agriculture (Xie et.al, 2018). In fact, energy and water are simultaneously effective on the rice production that means considering the water-energy nexus is necessary to analyse the environmental impacts associated with the rice production. Hence, it is required to consider energy and water in an integrated framework to mitigate environmental impacts of the crop production. Due to increasing population, required energy and water for agriculture have been raised in recent decades. Environmental degradations of the crop production might consist of two parts including Greenhouse gas (GHG) emission and environmental impacts on the water resources such as river ecosystem. The environmental impacts of agriculture on water resources and increasing GHG emission have been discussed in the literature (Hosseinzadeh-Bandbafha et.al, 2018). It is required to review on energy and water use and their environmental impacts.
As a description on the energy consumption in the agriculture, direct energy use such as fuel or electricity for operating machinery and equipment and indirect energy use such as the fertilizers and biocides have been highlighted as the sources of the energy consumption in the literature (Ilahi et.al, 2019). Minimizing energy use in the agriculture might be important to mitigate greenhouse gas (GHG) emission. In fact, agricultural productions produce 10% to 12% of the GHG emission in the atmosphere (Hosseinzadeh-Bandbafha et.al, 2018). However, reduction of energy consumption might decrease the yield of the farming that means an optimization system is needed in this regard. Data envelopment analysis (DEA) has been applied regarding the energy optimization in agriculture which is a linear programming approach for evaluating the efficiency of decision-making units (DMUs) (Khalili-Damghani et.al, 2015). Some previous studies focused on the energy use of the agricultural production in the orchards (Taghavifar and Mardani, 2015). Rice is one of the important crops that might have significant effect on the food security. Thus, rice might be considered as a strategic crop in many countries. Some previous studies focused on the energy consumption in the rice production in which different

geographical regions have been analysed. Analysing or optimizing the energy use was the main purpose in the previous studies regarding the rice production (Kazemi et.al, 2015).
Water use in agriculture might have significant environmental impacts as well. For example, using rivers as one of the important freshwater resources for supplying irrigation demand is prevalence in many countries (Koç, 2015). Thus, changing the instream flow would be effective on the yield of the rice production. It should be noted that increasing water demand in different sectors has raised offstream flow of the rivers that means instream flow has been reduced (Postel, 1998). In fact, river ecosystems are threatened due to lack of adequate instream flow that might reduce the suitability of the river habitats. All the available water in the rivers is not useable for irrigation demand that means environmental flow should be remained in the river. In fact, the environmental flow might protect the ecological sustainability of the river ecosystem. More details have been addressed in the literature (Yarnell et.al, 2020). Many methods have been proposed to assess environmental flow including hydrologic desktop methods, hydraulic rating methods, habitat simulation methods and holistic methods (Suwal et.al,2020; Tharme, 2003). It should be noted that some methods such as hydrological desktop methods are not reliable to assess environmental flow due to lack of focus on the regional ecological values. Conversely, holistic methods might be expensive. It seems that using habitat simulation methods might be logical in this regard (Tharme, 2003). In fact, these methods need limited ecological studies with a focus on the target species in the river ecosystem that means regional ecological values of the study area will be considered in the assessment of the environmental flow. Instream flow incremental methodology (IFIM) originally proposes the univariate physical habitat model in structure of the PHABSIM software that has been used in many previous studies (Nalamothu, 2021). However, this method has been criticized due to inability for simulating interactions between physical habitat parameters (Noack et.al, 2013). Hence, multivariate methods have been proposed to simulate physical habitat in the rivers. Multivariate fuzzy approach is one of the robust methods for simulating physical habitats that is able to simulate interactions between parameters. Moreover, this method is able to consider the expert opinions in the development of verbal fuzzy rules. Recent studies applied this method in the assessment of river ecosystem and environmental flows. More details have been addressed in chapter 4.

Climate change is a global problem in the world that might have considerable impact on the hydrological systems in the world (Middelkoop et.al, 2001). According to the literature, the number of extreme events such as floods or droughts might be increased in the hydrological systems such as river basins (Mendelsohn and Saher, 2011). Furthermore, hydrological modelling in many case studies corroborate the changing stream flows due to impact of climate change (Mohammadi et.al, 2020; Morid et.al, 2016). Different types of models could be used to simulate the impact of climate change on the rain fall in the river basins. More details regarding the climate change models have been addressed in the literature. The climate change might affect supply of irrigation demand and environmental flows. In other words, potential climate change impact might alter the crop production considerably. Farmers will try to use more available water in the rivers in the future droughts due to climate change for preventing reduction of crop production. However, consequent environmental impacts on the river ecosystems would be inevitable. Hence, we face a complex problem in the management of climate change impacts on the river ecosystem, energy use and yield of crop production. It seems that utilizing the water-energy-river ecosystem nexus approach to analyse and optimize energy and water use for the rice fields in which river is the water sources for supplying irrigation demand might be essential. Previous studies corroborated that artificial intelligence methods might be useful for simulating crop production in the agriculture. Artificial neural networks (ANNs) are one of the known methods that have been used as the data driven models (Bala and Kumar, 2017). Neural networks conventionally contain three layers including inputs layer, hidden layers and output layers in which a computational map between inputs and output(s) could be generated (Bala and Kumar, 2017). A robust data driven model based on the neural networks is advantageous for simulating complex issues such as crop yield in the agriculture. In fact, simple statistical models are not able to predict the yield. In contrast, neural networks might be a robust option in this regard. Some efforts have been carried out to improve the performance of neural networks. For example, neuro fuzzy inference systems have been recommended as an improved neural network model in which fuzzy inference system is applied in the structure of the neural network (Salleh et.al, 2017).

Integrated assessment and optimization of environmental impacts of water and energy use might be a challenge that was the main motivation of the present chapter. In fact, previous studies focused on the optimal energy use with highlighting environmental impacts of irrigation supply. However, water-energy nexus should be considered in an integrated assessment. This issue might be more challenging due to impact of climate change in the future years. Thus, the novelty of the present chapter is to develop a novel optimization framework in which environmental impacts of water- energy use and economic benefits of farming under the climate change condition could be balanced. Combining data driven models and evolutionary algorithms considering climate change models generate a framework that is more robust compared with previous studies for integrated environmental management of agriculture. To sum up, the objective of the present chapter is to mitigate environmental degradations due to water and energy use while the economic benefits of farming (yield) is maximized under the current condition and climate change impacts

## 6.2 Methodology

### 6.2.1 Overview on the methodology

Figure 6-1 displays the workflow of the proposed method in which four main parts are identifiable. First, impact of climate change on the stream flow is simulated to predict the future stream flow time series to the diversion dam where is responsible for supply of irrigation demand. Then, a data driven model is developed to predict rice field production in which water and energy use are the main inputs of the model. In the next step, ecohydrualic simulation is utilized to develop ecological impact function at the downstream river of the diversion dam in which fuzzy physical habitat simulation was applied. Finally, outputs of the simulations are applied in the structure of the optimization model in which three purposes were defined including minimizing energy use, mitigating ecological impacts on the river ecosystem and maximizing the yield of rice production.

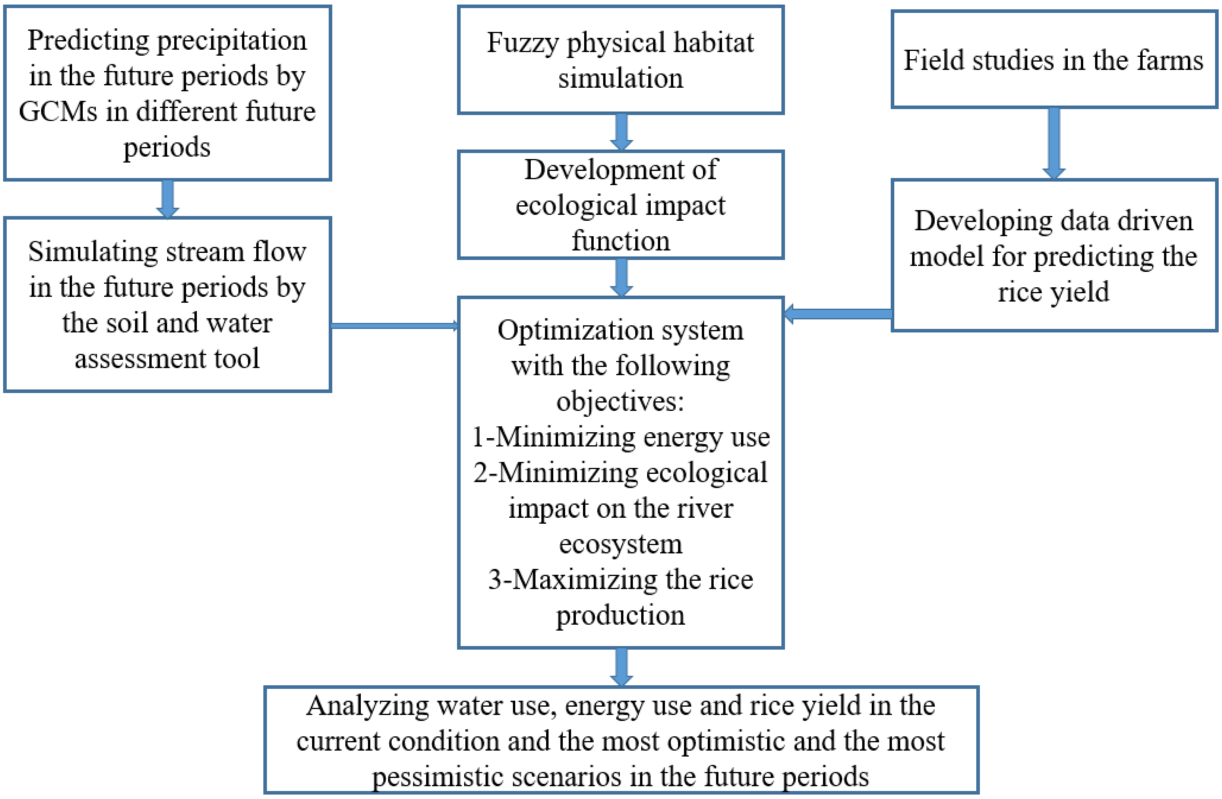



**Figure 6-1- Workflow of the proposed methodology**

### 6.2.2 Climate change impact assessment on the stream flow

This model contains two parts including assessing impact of climate change on the rainfall in the future periods and converting rainfall to runoff to simulate stream flow in the future years. The fifth assessment report by the IPCC in which the Coupled Model Intercomparison Project phase 5 (CMIP5) with four different RCP scenarios (RCP2.6, RCP4.5, RCP6 and RCP8.5) have been introduced was applied in the present chapter. More details have been addressed in the literature (e.g. Bayatvarkeshi et.al, 2020). General circulation models (GCMs) as one of the known methods to project the impact of climate change have coarser scale that means downscaling might be helpful to have more accurate results. Long Ashton research station weather generator (LARS-WG) was applied for downscaling that has been addressed in the previous studies (e.g. Bayatvarkeshi et.al, 2020). Precipitation was projected in the four 20-yearperiods (2021–2040, 2041–2060, 2061–2080 and 2081-2100) by the selected CMIP5s including CanESM2 (CM1), MIROC5(CM2) and NorESM1-M (CM3) for RCP 4.5 and RCP8.5. In the next step, the runoff routing model was utilized to simulate stream flow in the future period. Soils and water assessment tool (SWAT) as a familiar tool for simulating stream flow was used in this regard. Figure 6-2 displays the flowchart of this model to simulate stream flow. The calibration and validation process of the model was carried out using SWAT-CUP as a standalone software that is developed for this purpose. Methodology of SWAT and optimization process by the SWAT-CUP have extensively been described in the literature (Pradhan\ et.al, 2020). It is also required to use some indices for measuring the performance of the model. In the present chapter, we applied two indices including NSE and RMSE to measure the robustness of the model for simulating stream flow as displayed in the following equations. More details regarding RMSE and NSE have been addressed in the literature (Brassington, 2017; McCuen et.al, 2006)

$$RMSE = \sqrt{\sum_{I=1}^{T} \frac{(O_t - M_t)^2}{T}} \quad (1)$$

$$NSE = 1 - \frac{\sum_{t=1}^{T}(M_t - O_t)^2}{\sum_{t=1}^{T}(O_t - O_m)^2} \quad (2)$$

where $O_t$, $M_t$ and $O_m$ are observed flow, modelled flow in each time step and average of the observed flows in each microhabitat respectively.

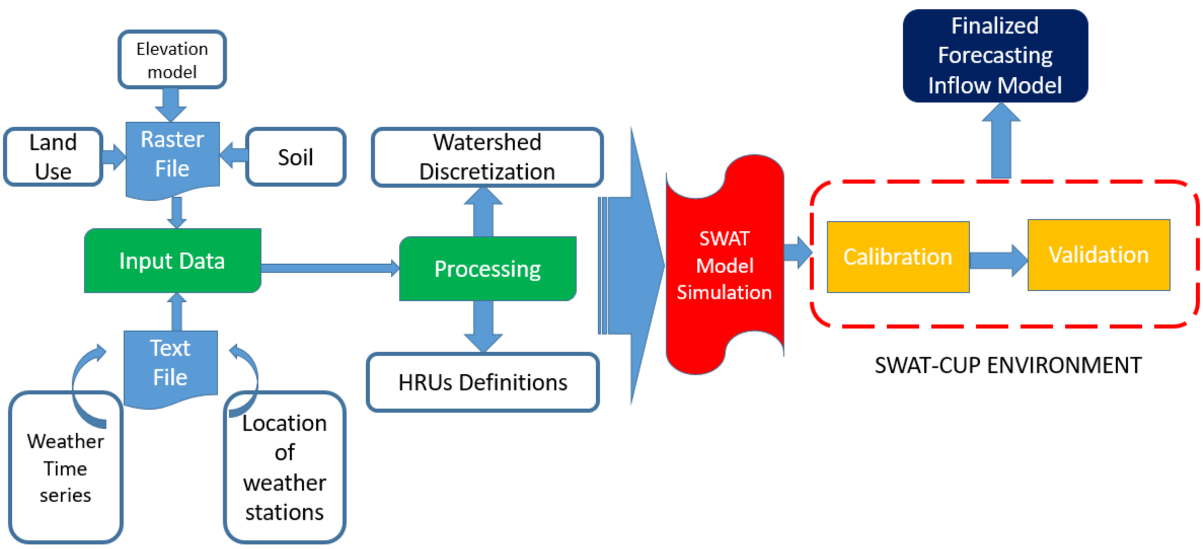



**Figure 6-2- Workflow of coupled SWAT and SWAT-CUP to simulate outflow of catchment**

### 6.2.3 Modelling rice yield

The main effective parameters on the rice yield are inputs of the energy consumption and water use. Other factors might be effective on the production. However, we assumed that other factors are suitable and will not be changed in the study area that might be a logical assumption. Development process of the data driven model of the rice yield includes two sections. In the first section, the field studies were carried out in the study area in which questionnaire was filled by the farmers. In the questionnaire, farmers should fill the energy inputs for rice production, water use and yield of the production. More than 100 farms were selected in the field studies in which farmers helped the research team to record accurate results from the rice production in the study area. Then, energy inputs were converted to the total consumed energy considering energy equivalent coefficients as displayed in the table1. Equation 3 was used to compute total energy consumption. In the next step, An ANFIS based model was developed to predict the rice yield in which water and energy use are inputs of the model and the yield of the production (Kg/Ha) is the output of the model. This model was applied in the structure of the optimization system. Subtractive clustering was used in the ANFIS based model. Moreover, hybrid algorithm was used in the training process of the data driven model. Equation 3 was used to compute total energy use in which $F_i$ is effective input of the energy use and $C_i$ is energy equivalent coefficient and I is total number of the inputs. Moreover, TE is total energy use in MJ/Ha. In other words, equation 1 computes total energy consumption in the area unit of the farm.

$$TE = \sum_{i=1}^{I} F_i . C_i \qquad (3)$$

### 6.2.4 Ecological impact function of river ecosystem

Fuzzy physical habitat simulation was utilized to develop the ecological impact function in the river ecosystem. Two steps are required in this method. First, field studies and using expert opinion to develop verbal fuzzy rules. Secondly, combining fuzzy rules with one-dimensional hydraulic simulation to develop ecological impact function. A representative reach with length of 1000 meters was selected at downstream of the diversion dam in the case study for field studies and habitat simulation. Fish observations were carried out by electrofishing method as one of the applicable methods for ecological field studies in the river habitats. Moreover, velocity, depth and substrate were measured in the sampling points. Furthermore, cross sections were surveyed for the hydraulic simulation purpose. More details regarding the methodology of field studies and measurements have been addressed in the literature. The representative reach was simulated by HEC-RAS 1D model in the steady state for different stream flows. Chapter 4 presented more details on the fuzzy physical habitat simulation.

### 6.2.5 Optimization system

The main component of the developed optimization system is objective function in which three purposes were considered including 1- minimizing energy use for reducing GHG emission in the study area 2- mitigating ecological impact on the river ecosystem due to supply of irrigation demand and 3- maximizing the yield of production. First, the optimization model was applied in the current condition and then different scenarios of the climate change were applied in the optimization model. The outputs would demonstrate how the developed system is able to manage impact of climate change on the rice production while environmental impacts are alleviated. Outputs of the simulations were applied in the structure of the optimization system. Equation 4 displays the developed objective function in the presents study. The average year of 20 years period in the current condition and the future periods was simulated by the optimization model. Hence T is 12 months for each optimization process by the model.

$$Minimize(OF) = ((\sum_{t=1}^{T}(\frac{NWUA_t - OWUA_t}{NWUA_t})^2)/T) + (\frac{1}{\frac{OPY}{MXY}}) + \frac{OPE}{MXE} \quad (4)$$

where NWUA is natural weighted useable area in the river, OWUA is optimal weighted useable area in the river, OPY is optimal yield of the crop production, MXY is maximum yield of the crop production observed in the field studies, OPE is optimal energy use and MXE is maximum energy use observed in the field studies. Each optimization model might need some constraints that should be defined based on the purposes and requirements of the model. In the proposed optimization system, three constraints should be defined including minimum water use or irrigation demand for the rice production, maximum water use for rice production and minimum and maximum energy consumption for rice production in the study area. More details reading the considered values for these constraints will be presented in the next section. Moreover, environmental flow should not be more than available water in the river. Penalty function is a known method to convert the constrained optimization problem to unconstrained one that has been used in many previous optimization models of the water resource management. Due to advantages of this method for applying in the structure of the evolutionary optimization, this method was utilized in the present chapter. Thus, five penalty functions were added to the optimization model as displayed in the following equations.

$$if\ OPE > MXE \rightarrow P1 = c1\left(\frac{OPE-MXE}{MXE}\right)^2 \quad (5)$$

$$if\ OPE < MIE \rightarrow P2 = c2\left(\frac{OPE-MIE}{MIE}\right)^2 \quad (6)$$

$$if\ OPI > MXI \rightarrow P1 = c3\left(\frac{OPI-MXI}{MXI}\right)^2 \quad (7)$$

$$if\ OPI < MII \rightarrow P2 = c4\left(\frac{OPI-MII}{MII}\right)^2 \quad (8)$$

Equations 4 to 8 have been developed in the present chapter. Some assumptions were considered for developing the above equations (4 to 8) and running the optimization model. First, physical habitat loss is the main effective factor in the ecological assessment of the river ecosystem. Secondly, water and energy use are the key parameters for the rice production in the study area. Thirdly, mathematical and technical constraints as defined in the equations are needed to improve the performance of the optimization model. Particle swarm optimization (PSO) as one of the known classic evolutionary algorithms was utilized in the present chapter to minimize the objective function. More details are available in chapter 3.

### 6.2.6 Case study

The proposed framework was implemented in the Talar river as one of the known rivers in the Mazandaran province, Iran. Mazandaran is one of the northern provinces in Iran where is a known place for cultivating rice due to high humidity and appropriate temperature. In fact, the main economic activity for the people in Talar river basin is agriculture with a focus on the rice production. On the one hand, Due to proper price of rice, farmers are willing to maximize the yield of production without considering environmental degradations in the region. On the other hand, environmental managers have serious concerns in terms of three aspects. First, GHG emission is a general environmental concern in the province that means minimizing energy use in the agriculture is helpful for increasing environmental sustainability. Secondly, several valuable native fish species live at the downstream of diversion dam that is responsible for supply of irrigation demand. In fact, increasing offstream flow might reduce the instream flow considerably that destructs the valuable aquatic habitats in the river. Thirdly, the impact of climate change on the environmental sustainability of the river basin is ambiguous that might raise the environmental destruction in the future years. The environmentalists and farmers face complex problem that might not be manageable easily. In other words, negotiations between farmers as the stakeholders and environmentalist might be escalated due to complexities in the management of the environment. It seems that an integrated framework for managing climate change impacts in which yield of production is maximized while GHG emission and ecological impacts on the river ecosystem are mitigated. In fact, this framework is able to reduce environmentalists and farmers' concerns under the current condition and potential impact of climate change. Figure 6-3 displays the location of Talar basin, river network, location of diversion dam at downstream and land use. The rice fields at downstream of river could be observed that their irrigation demand is supplied using water diversion project. According to the recommendations by the regional agricultural department, minimum energy use, maximum energy use, minimum water use, maximum water use were defined 13481 MJ/Ha, 60897 MJ/Ha, 1050 m3/s and 3940 $m^3$/s.

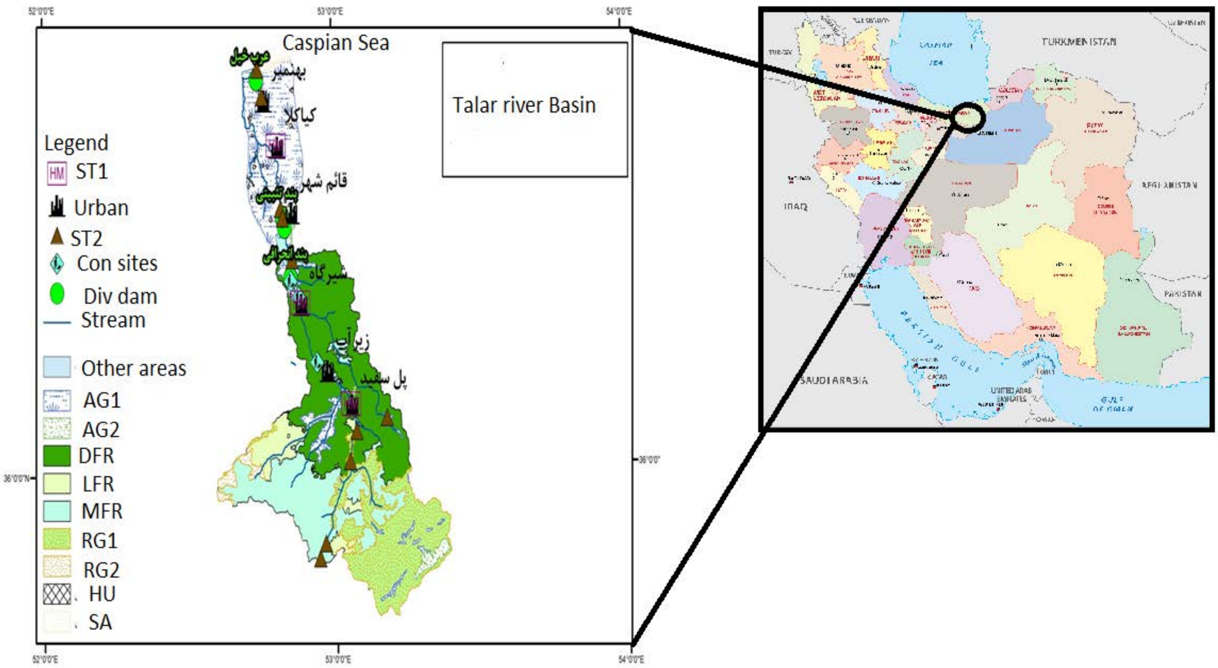



**Figure 6-3- Location of the Talar river basin, stream network and land use**

## 6.3 Results and Discussion

It is necessary to present outputs of the simulations and optimization in the proposed method. Relevant interpretation and discussion on the results will be presented for each part of results. First, the outputs of the rainfall-runoff modelling are presented. Figure 6-4 displays the validation of the SWAT output in which RMSE and NSE are displayed in this figure. Moreover, it is necessary to present results of fuzzy physical habitat simulation in the simulated river reach at downstream of diversion dam where is responsible for supplying irrigation demand. Table 1 displays part of the verbal fuzzy rules based on developed methodology for physical habitat simulation.

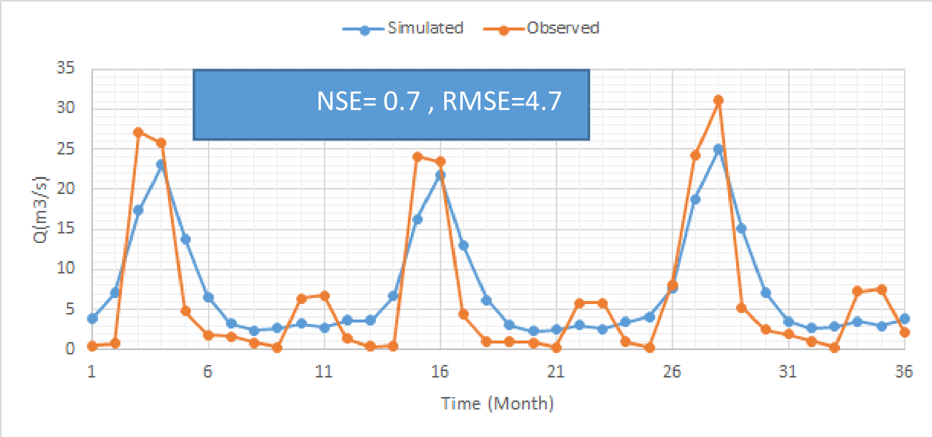



**Figure 6-4- Validation output of the SWAT**

**Table 6-1- Part of developed verbal fuzzy rules for the target species (*Capoeta capoeta*)- total number of rules are 27)**

| Rule Code | Depth | Velocity | Substrate | Habitat suitability |
|---|---|---|---|---|
| CR1 | *M* | *L* | *M* | *L* |
| CR2 | *H* | *L* | *M* | *H* |
| CR3 | *L* | *L* | *M* | *L* |
| CR4 | *H* | *M* | *H* | *M* |
| CR5 | *L* | *M* | *H* | *H* |

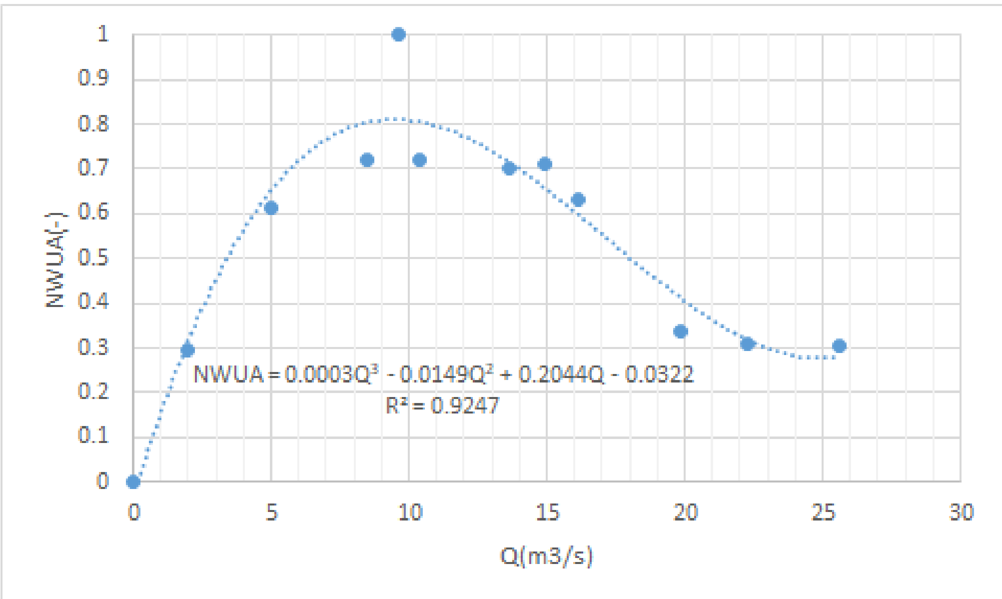



**Figure 6-5- The final output of fuzzy physical habitat simulation in the river ecosystem**

It seems that the developed runoff routing model is reliable for using in the further applications due to robust predictive skill of the model. In fact, if the NSE is more than 0.5, the predictive skill of the model is robust and reliable. It is essential to compare result of SWAT in the present chapter and previous studies. The final output of physical habitat simulation (i.e., the ecological impact function) is displayed in the figure 6-5. In fact, this function defines the relationship of normalized weighted useable area respect to the river flow that might be useable as the environment index to assess ecological degradation in the river ecosystems. As an interpretation on the physical habitat simulation in the case study, the impact of flow velocity on the physical habitat suitability is considerable that means the flow velocity is effective on the energy consumption by the fish. Depth and substrate will affect the habitat suitability as well. However, our observations and expert opinions demonstrated that flow velocity is more important than two other parameters in the case study. It should be noted that the outputs and conclusions on the fuzzy physical habitat simulation is only applicable for the target species in the case study. It is recommendable to apply other methods of physical habitat simulation in the future studies.

The predicted mean stream flows in the simulated period by different climate change models in all the scenarios are not displayed for having concise presentation on the results. However, interpretation on the impact of climate change on the rive flow is explained for clarifying how the climate change might have impact on the stream flow in the case study. Results of stream flow simulation in the future periods corroborate the considerable impact of climate change on the stream flow in the case study. In fact, simulation of climate change impact on the irrigation supply is not negligible for optimal management of agriculture in the case study.

The results of optimization model should be presented and interpreted as well. Moreover, it matters to discuss how the optimization model can carry out defined responsibilities. Figure 6-6 shows the results of the optimization model in terms of mitigating ecological impacts on the river ecosystem. As a general interpretation on this figure, the physical habitat loss in the natural flow is averagely 0.55 while the physical habitat loss in the optimal environmental flow is averagely 0.7. In fact, physical habitat loss by the optimization model is 0.15 that seems logical and acceptable. Results indicate that the optimization model provided a fair balance for the river ecosystem in all the climate change scenarios. In other words, it provides a sustainable ecological status for all the climate change scenarios. However, it is not able to increase the suitability as well as the physical habitat suitability in the natural flow. In other words, it is not expectable to simulate the physical habitat like the natural flow in the optimization system. The developed optimization system is a multipurpose model that should support environmental requirements as well as protecting rice production in the study area.

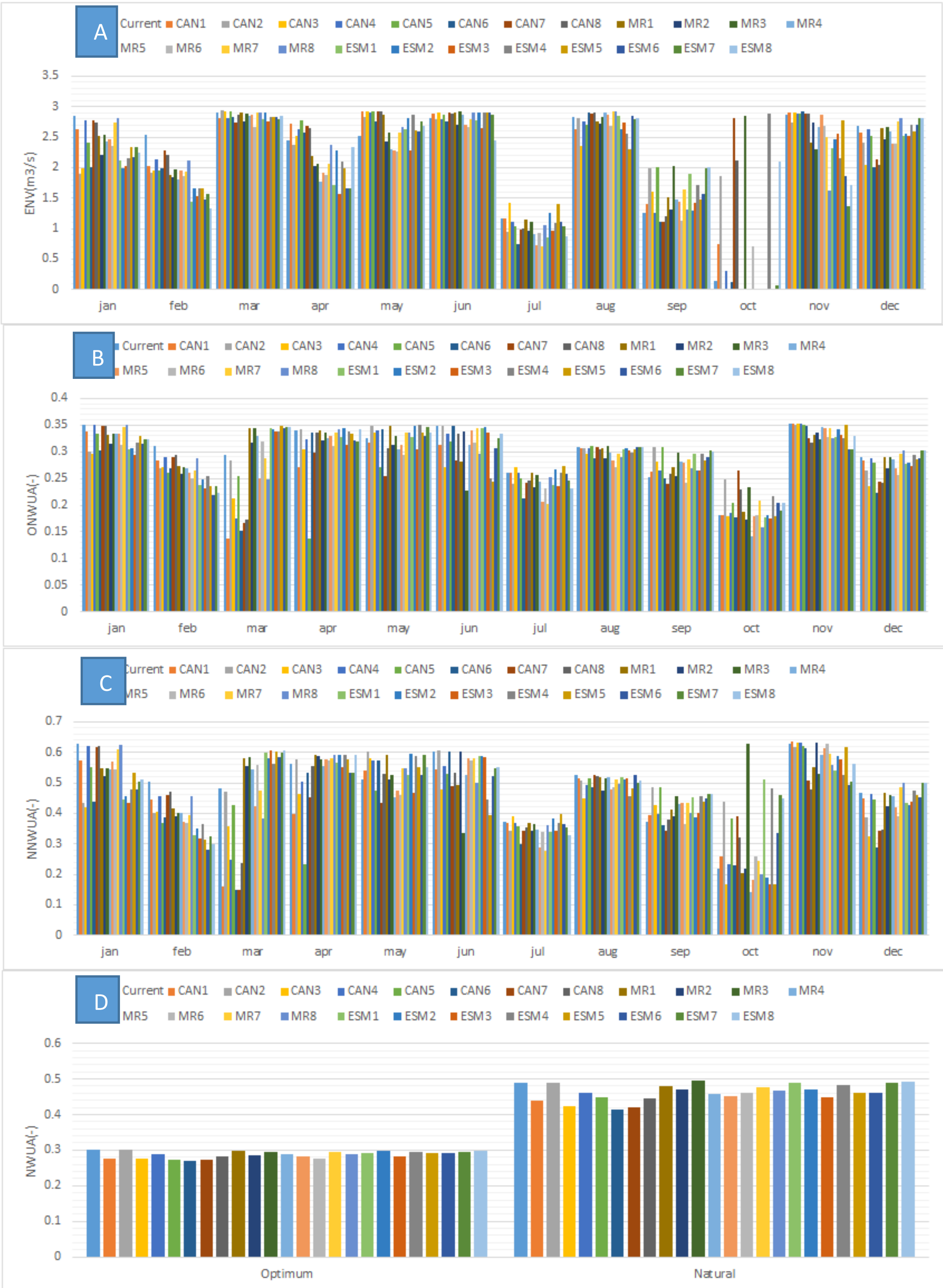



**Figure 6-6- Outputs of the optimization model regarding mitigation of ecological impacts in the river ecosystem (A: optimal river environmental flow, B: optimal normalized weighted useable area generated by the optimization model, C: normalized weighted useable area in the natural flow in other words no irrigation supply by river and D: comparing normalized weighted useable area in the optimal water supply and natural flow)**

Another environmental purpose for the model is to minimize energy use for the agriculture. In fact, the optimization model should be able to mitigate ecological impact on the river ecosystem and energy use while the rice production should not be reduced considerably under the impact of climate change. Figure 6-7 shows the performance of the optimization model in terms of water and energy use and rice production. The optimization model tried to adjust the energy use to maximize the yield of the rice. The optimal solution in the current condition and potential impact of climate change in terms of rice production is the same that means the optimization model is able to mitigate the impact of climate change on the rice production. However, the energy use is increased in some scenarios. Increase or decrease of energy use means changing the inputs such as fertilizers. As interpretation on the figure 6-7, it seems that the optimization model excellently carried out the defined purpose. In fact, water consumption or irrigation supply is changed based on available stream flow in different climate change scenarios considering the environmental flow in the river. The results of the simulations and optimization demonstrate that the climate change might alter the offstream flow or irrigation supply by the river considering ecological impacts on the river ecosystem which is challenging. However, the proposed model could balance the water and energy consumption for protecting the rice production.

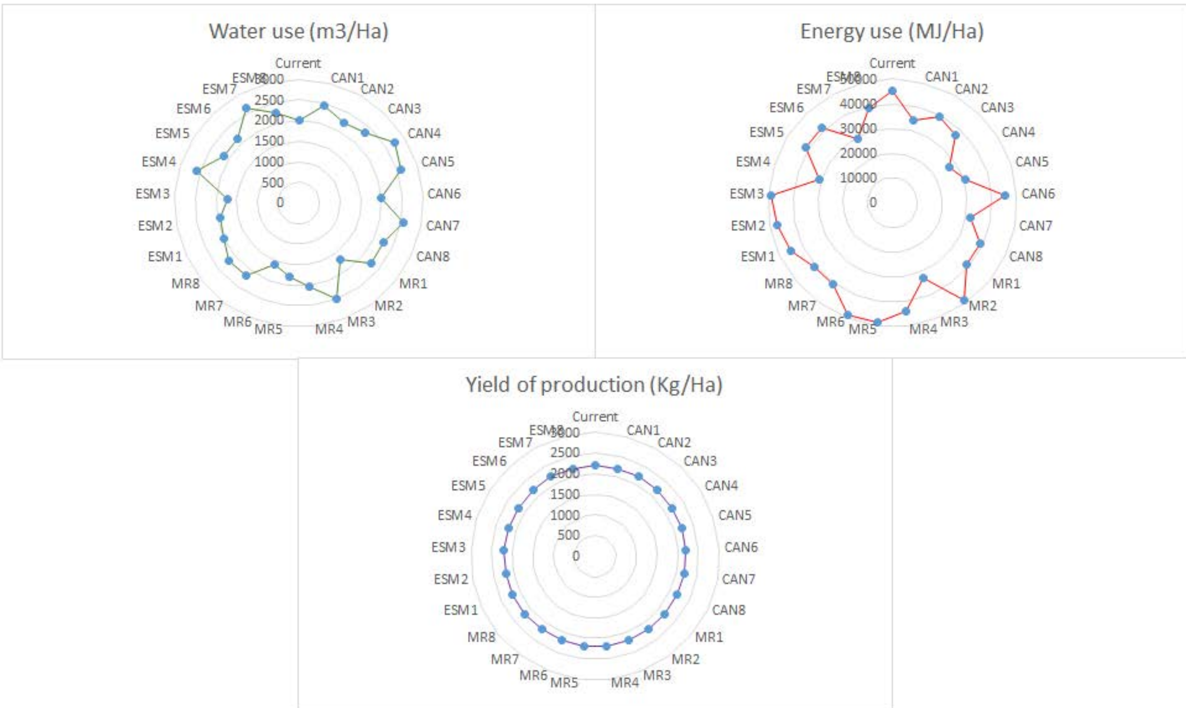



**Figure 6-7- Balancing the water and energy use and rice yield by the optimization model in different scenarios**

It is also required to investigate how changing the energy use would affect the inputs of the agriculture. We considered the most optimistic scenarios (OPT scenario) and the most pessimistic scenario (PES scenario) in which energy consumption is minimum and maximum respectively. According to the results, the optimal energy use in the current condition and OPT and PES scenarios are 45227, 27169 and 48839 MJ/Ha respectively. In other words, the climate change reduces the energy consumption in the OPT scenario in which more water is available for the irrigation. Conversely, the optimization system increases the energy use in the PES scenario for adjusting the yield of the rice. It seems that the impact of climate change on the rice production is not significant. The optimization model did not need to increase the energy use in the PES scenario. Interestingly, it sounds that the climate change might be helpful to increase the irrigation supply that might lead to reducing GHG emission by the agriculture in the case study. Table 2 displays the proposed inputs of the energy use for the rice production in three conditions including current condition, OPT scenario and PES scenario. It seems that the energy inputs are reduced more than 30% in the OPT scenarios that indicates the applicability of the proposed method. Moreover, the consumption of inputs such as fertilizers is slightly increased in the PES scenario. It should be noted that the results of the present chapter are not reliable for using in other regions even if the climatic condition is like the case study of the present research. In other words, all the developed models including the climate change modelling, the ecological impact function and predicting rice production should be carried out based on the local data. However, the framework of the optimization system might not need to be changed. The results of the present chapter corroborate the robustness of the model in the future applications. Moreover, this model could be extended for other crops as well. However, the structure of the yield prediction model should be changed based on the requirements of the crop. For example, the requirements of predicting the yield of orchards' crops are not the same with the annual crops such as rice.

**Table 6-2- Proposed optimal energy inputs in three conditions including current condition, the most optimistic scenario and the most pessimistic scenario in the future**

| Inputs | Unit | Energy equivalent coefficient (EEC) (MJ/unit) | Current | OPT scenario | PES scenario |
|---|---|---|---|---|---|
| Labour | H | 1.96 | 392.75 | 235.93 | 424.12 |
| Machinery | H | 62.70 | 13949.41 | 8379.66 | 15063.29 |
| Diesel | L | 56.31 | 19032.57 | 11433.20 | 20552.35 |
| Nitrogen | Kg | 66.14 | 7927.84 | 4762.40 | 8560.89 |
| Phosphorous | Kg | 12.44 | 1064.47 | 639.45 | 1149.47 |
| Potassium | Kg | 11.50 | 590.42 | 354.68 | 637.57 |
| Zinc | Kg | 8.40 | 28.75 | 17.27 | 31.05 |
| Biocides | Kg | 15.30 | 117.96 | 70.86 | 127.38 |
| Electricity | kWh | 11.93 | 2123.34 | 1275.53 | 2292.89 |

Different aspects of the developed model should be discussed as well. Each model might have some advantages, drawbacks and limitations that should be considered in the applications. The proposed method comprises four main parts including climate change modelling, ecological impact assessment, simulating rice production and optimization system that should be considered in the discussion. First it should be clarified how the proposed model could be useful for stakeholders. On the one hand, the main advantage of the proposed optimization model for the farmers as the stakeholders in the study area is how the model is able to mitigate potential impact of climate change on the rice production. On the other hand, environmental managers are willing to minimize environmental degradations by the optimization model. As presented, the optimization model properly mitigated the physical habitat loss in the river ecosystem in the current condition and impact of climate change. Results indicated a complex relationship between the impact of climate change on the irrigation supply and energy use in the case study. It should be noted that the case study of the present research is a humid region in Iran. According to the climatic studies in Iran, most of the available areas are in the arid and semi-arid regions. However, two northern provinces including Mazandaran province and Guilan province are in the humid area that means the impact of climate change on the precipitation in these provinces might be different from other regions. The climate change might exacerbate the humidity of the humid regions and aridity of the arid regions in the future years. However, climate change modelling is essential in all the regions to judge on the future condition. Based on the climate change modelling in the case study, considerable increase of precipitation might be possible in the future years. In other words, the climate change effect could be used positively to manage the GHG emission by the agriculture. In fact, increasing precipitation in the optimistic scenarios of climate change might be helpful to reduce inputs of energy use in the rice production such as fertilizers.

Moreover, the results of the present chapter demonstrate that the impact of climate change on the agriculture might be complex and simulation of the effects in different regions is necessary. On the one hand, the proposed method could reduce energy use or GHG emission of the agriculture in the optimistic scenarios. On the other hand, it could protect rice production in the study area by adjusting or increasing the energy consumption in the pessimistic scenarios in which irrigation supply could be diminished. In fact, the proposed optimization model could utilize the positive effects of climate change on the precipitation to reduce the GHG emission in the case study. It indicates that the application of optimization systems of the climate change impacts in the regional scale could be helpful for better management of the agriculture toward the environmental sustainability.

More details regarding methodology of the present chapter should be discussed. We applied the coupled GCM-SWAT to simulate the stream flow in the future periods. This system has extensively been used in the previous studies that indicated the reliability of this method. However, it might not be applicable in all the cases due to need for extensive data such as land use and digital elevation model. Hence, it is recommendable to apply other methods such as machine learning methods for cases in which adequate data is not available for hydrological simulation of run off. Furthermore, we applied the fuzzy physical habitat simulation in the assessment of the ecological impacts or development of the ecological impact function. However, this method is not applicable in all case studies. In other words, using expert opinions by the experienced ecologist is one of the requirements for developing the verbal fuzzy rules in this method. If it is not possible to apply this method for developing the ecological impact function, other methods could be replaced. For example, neuro fuzzy inference system could be one of the good options for cases in which fuzzy physical habitat simulation is not useable. Furthermore, it should be noted that water quality was not considered in the assessment of the ecological status of the river ecosystem in the case study. However, it might be necessary to add the water quality models to the ecological impact function in other case studies. Hence, we recommend focusing on adding water quality to the ecological impact function in the future studies.

Optimization system is another important aspect that should broadly been discussed. We developed a single objective optimization model in the present chapter that is able to simulate all the losses by applying a single objective function. At the first glance, it seems that using a multiobjective algorithm might be a good option to handle the designed optimization problem. The developed objective function contains different independent terms that means each term could be considered as a standalone function. However, two serious disadvantages might confine the application of multiobjective optimization algorithms. First, computational limitations are the first disadvantage of the multiobjecive optimization. In the computer science, the computational complexities of the optimization algorithms are defined as the needed time and memory to present an optimal solution. High computational complexities might make the optimization problem cumbersome. In fact, it is required to carry out the numerous simulations or having simulation for a long-term period in the real projects. Hence, it is expected that high computational complexities reduce the engineers' willingness for applying the proposed optimization system. In the present chapter, the data driven model was applied in the structure of the optimization model that increases the computational complexities for the system. Multiobjective algorithms inherently have higher computational complexities compared with the single objective optimization algorithms that means more time and memory might be needed for finding the best solution. Hence, the developed single objective function in the present chapter might be advantageous in this regard. Moreover, the limited number of multiobjective optimization algorithms has been developed in the literature that might confine the application of these algorithms. In fact, one of the drawbacks of the evolutionary algorithms is inability to guarantee the global optimization that means using different algorithms might be helpful to find the best solutions. Hence, it might not be proper to use the multiobjective algorithms in the proposed optimization model. Utilizing the single objective function is beneficial for applying a wide range of evolutionary algorithms in the optimization process.

Some points should be discussed for clarifying how the results of the optimization system could connected. Furthermore, advantages of the proposed method regarding the economic benefits of agriculture should be emphasized as well. The results of the proposed optimization system under the current condition and climate change impacts consist of three parts including optimal water use, optimal energy use and optimal production. The optimal water use means the ecological impacts on the river ecosystem as the water resource are alleviated. Thus, the optimal water use could reduce concerns regarding ecological impacts of water supply. Moreover, the optimal energy use is able to minimize environmental concerns regarding the greenhouse gas emission due to farming. In contrast, optimal crop production (yield) is able to minimize the farmers' concern regarding the reduction of benefits due to alleviating environmental impacts under the current condition and impact of climate change. Another should be discussed is how the proposed optimization model could be advantageous in terms of agricultural benefits. As displayed in the figure 6-7, rice production is the same in all the scenarios that means the optimization model could protect the farmers' revenue properly. In fact, if reduction of environmental impacts is aimed, the crop production might be reduced without using an integrated framework. Decreasing water and energy use is effective on the crop production that means diminishing crop production is predictable in the absence of integrated optimization framework. However, the proposed system in the present chapter is able to minimize farmers' concerns reading reduction of revenue due to alleviating environmental impacts of water and energy use.

We recommend utilizing the proposed method for facing challenges of the climate change in the agricultural production. The proposed framework corroborates the strong relationship between water and energy for the agricultural production. In other words, using water-energy nexus approach is necessary for assessing the agricultural production. A balance between water and energy use is useful to mitigate impact of climate change on the agricultural production. The present chapter proposed a principal optimization framework to mitigate impact of climate change on the rice production in which many improvements could be carried out in the future studies. In fact, it might open new windows on the application of hydrological models, environmental models and optimization algorithms for managing the impacts of climate change on agriculture and increasing environmental sustainability in the river basin scale. A point should be noted for the future studies. In the case study, water and energy are the main variables for changing the rice production. In other words, other factors are acceptable that might reduce the complexities of the model. However, it might be needed to add other factors such as social aspects and climatic condition to the model. It should be noted that we assumed that the temperature for cultivation of the rice in the future periods is acceptable like the current condition. Hence, improvement of the yield prediction model is necessary in the future studies that might increase the applicability of the proposed method. It should be noted that the proposed model in the present chapter is a novel combined model that could be improved based on the needs of other case studies.

## 6.4 Summary

The present chapter proposes a framework to mitigate impact of climate change on the rice production by maximizing the yield while the energy use and ecological impacts on the river ecosystem as the irrigation source are mitigated. Coupled general circulation model- soil and water assessment tool (SWAT) was utilized to project the impact of climate change on the stream flow. Fuzzy physical habitat simulation was applied to develop the ecological impact function of the river. Moreover, a data driven model was developed to predict the rice yield through changing water and energy consumption. Finally, all the simulations were utilized in the structure of the optimization model in which minimizing loss of the production, greenhouse gas emission by reducing energy use and physical habitat loss were considered as the objectives. Based on the results, the Nash–Sutcliffe model efficiency coefficient of the SWAT is 0.7 that demonstrates its reliability for simulating the impact of climate change on river flow. The optimization model is able to reduce the impact of climate change on yield of production by balancing water and energy use. In the most pessimistic scenario, water use should approximately be reduced 25% for protecting river ecosystem. However, the optimization model approximately increased energy use 16% for preserving the yield of the rice. Conversely, model decreased the energy use 40% compared with the current condition due to increasing water supply. Moreover, physical habitat loss is less than 50% that means the combined optimization model is able to protect river habitats properly.

# Chapter 7: Environmental operation of reservoirs considering downstream water quality requirements

Full contents of this chapter have been published and copyrighted, as outlined below:

Sedighkia, M., Datta, B. and Abdoli, A., 2022. Reducing impacts of rice fields nitrate contamination on the river ecosystem by a coupled SWAT reservoir operation optimization model. Arabian Journal of Geosciences, 15(2), pp.1-20.

## 7.1 Introduction

Nitrogen is found in several different forms in terrestrial and aquatic ecosystems including ammonia (NH3), nitrates (NO3), and nitrites (NO2). Nitrates in excess amount is considerably detrimental for aquatic ecosystems. High amount of nitrates and phosphorous would accelerate eutrophication. Moreover, excess nitrates can reduce level of dissolved oxygen (Burt et.al, 2011). Hence, high level of nitrates could be detrimental for aquatics such as fish and macroinvertebrates. Source of nitrates contain wastewater treatment plants, runoff from croplands or animal storage areas and industrial discharges (Xue et.al, 2016). Excessive use of chemical fertilizers might be one of the sources of nitrate contamination in the basins (Ostad-Ali-Askari et.al, 2017). Rice field is one of the main sources of nitrates in river basins (Ehteshami et.al, 2016). It should be noted that due to remarkable economic benefits of rice, it is an important crop in many countries. Hence, reducing impact of nitrate contamination to protect aquatic habitats is one of the important purposes in an integrated river basin management especially in areas in which nitrate contamination is the main source of water quality crisis. Thus, modelling of nitrate in the catchment scale is a key tool to simulate and manage contamination. Soil and water assessment tool (SWAT) is a continuous hydrologic simulator that is able to simulate outflow of catchment. Furthermore, it is able to simulate water quality parameters at the outflow of the catchment. This model has been used to simulate outflow of the catchment and water quality parameters (Arnold et.al, 2012). Many previous studies corroborate its abilities to simulate flow and water quality (e.g Cambien et.al, 2020; Wang et.al, 2019). The most important advantages of this model is continuous simulation. Using continuous simulation has been recommended by Australian rainfall and runoff 2016 (ARR 2016) to improve results of hydrological simulations (Balls et.al, 2016). Moreover, importance of water quality modelling in the surface and groundwater in the structure of hydrological modelling has been highlighted in the previous studies (e.g. Ostad-Ali-Askari et.al, 2021)

Large dams are the most important hydraulic structures in the river basins. They have significant role for economic development of urban and rural areas (Altinbilek, 2002). Management of reservoir operation may be a complex task for engineers. In other words, maximum benefits must be achieved due to high expenses of dam construction. Hence, optimizing reservoir operation is a highlighted topic in water resource management (Ahmad et.al, 2014). Moreover, climate change might make the management of water resource more complex (Ostad-Ali-Askar et.al, 2018). Hashimto et.al, 1982 developed an applicable form of the loss function that has been utilized as the objective function in many recent studies (e.g Ehteram et.al, 2018). Moreover, Datta and Burges ,1984 underlined that not only loss of release could be important but also storage loss must be taken into account in a reservoir optimization model. In other words, deviation from optimal storage might reduce the reservoir benefits. Furthermore, Hashimoto et.al, 1982 proposed three system performance indices including reliability, vulnerability and resiliency to measure performance of the optimization model. In fact, these indices assess the robustness of reservoir operation model. Most of the reservoirs are multipurpose which means other purposes such as flood control and hydropower electricity supply might be considered in the optimization of reservoir operation as addressed in the literature (e.g Jahandideh-Tehrani et.al, 2015). Furthermore, water quality control using optimal operation might be defined as the purpose of reservoir. However, it is not a primitive purpose for many constructed dams. Dhar and Datta, 2008 used elitist-genetic algorithm-based in the structure of a simulation–optimization model to optimize reservoir operation for controlling downstream water quality unsuitability. More studies have been addressed in the literature regarding optimal reservoir operation considering water quality purposes (e.g Kerachian and Karamouz, 2006; Shirangi, et.al, 2008; Amirkhani et.al, 2016; Castelletti et.al, 2014; Azadi et.al, 2019).

Two challenges should be noted in the reservoir operation optimization including forecasting inflow and defining optimization model. In fact, reservoir operation needs a robust forecasting inflow model. Two main types of models have been utilized to forecast inflow including run off routing models and data-driven models. Using a robust continuous run off routing that might cover a long-term period of reservoir operation is a requirement for optimal reservoir management. If water quality modelling is necessary as a purpose of the reservoir optimization, it should be incorporated with hydrologic inflow model in an integrated model to make the highest efficiency. Moreover, optimization method is another important issue to optimize operation. Linear programming was the simplest solution to optimize reservoir operation (Reis et.al, 2006). Due to non-linear nature of the reservoir operation, non-linear programming and dynamic programming were other mathematical models that have been addressed in the literature (Ahmad et.al, 2014). Novel computational solutions such as evolutionary or evolutionary algorithms have broadly been used as the optimization methods for the reservoir operation (e.g Afshar et.al, 2007; Afshar et.al, 2011; Yaseen et.al, 2019). It should be noted that different types of optimization models have extensively been used in the water engineering problems such as environmental issues or irrigation management in the droughts (e.g., Javadinejad et.al, 2019, Ostad-Ali-Askari, et.al, 2017).

The present chapter proposes a robust simulation-optimization method to reduce impact of nitrate contamination of rice fields at downstream river ecosystem. The main novelty of this study is to link the continuous hydrological model for simulating flow and water quality to the reservoir operation optimization. In fact, continuous hydrological modelling is coupled with artificial intelligence method to manage water quality in the river ecosystem. Another novelty is to integrate purposes of the conventional reservoir operation model and environmental impacts of rice field runoff. Moreover, an applicable hierarchical system is proposed to finalize the optimal release from the reservoir. Simulated river basin contains rice fields at downstream areas of reservoir. Due to high irrigation demand by vast agricultural lands, supply of water demand increases challenges. Hence, a complex simulation-optimization method was designed to minimize water demand loss, storage loss and impact of nitrate contamination at downstream river reach. We used different evolutionary algorithm to solve defined objective function. Furthermore, different system performance indices were utilized to measure the robustness of reservoir operation optimization. Finally, a decision-making system was applied to select the best algorithm. Results and analysis of present chapter are helpful for designing an integrated system that might be aimed to maximize benefits of reservoir beyond initial defined purposes of reservoir.

## 7.2 Application and methodology

### 7.2.1 Overview on the methodology

The proposed method is a combined approach. Hence, an overview on the methodology might be helpful for the readers. Figure 7-1 displays the workflow of the proposed method. More details regarding each part will be presented in the next sections.

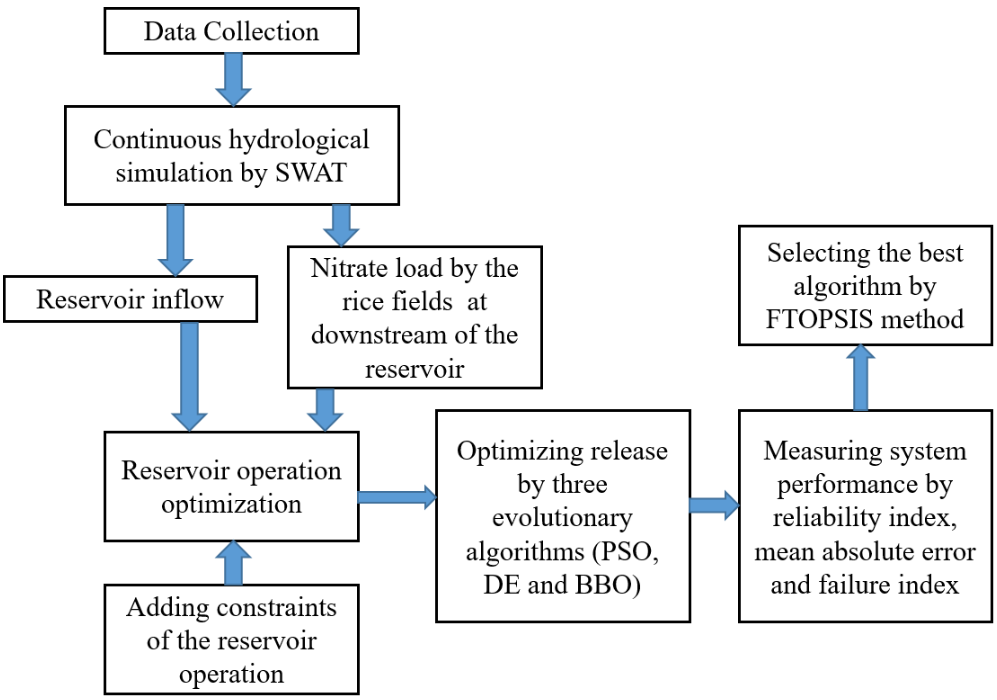



**Figure 7-1- Workflow of the proposed method**

### 7.2.2 Study area

The Tajan river basin at northern region of Iran was selected for implementing the proposed framework. This river is one of the largest rivers in southern Caspian Sea basin that is located in the Mazandaran province. Major economic activity of the residents in this river basin is agriculture. Due to the suitable climatic condition at downstream region of the Tajan river basin, rice is the major crop for many farms. Cultivation of rice is very important in Mazandaran province based on two reasons. First, it increases the farmers' income remarkably. Thus, they try to maximize area of rice fields in this area as much as possible. Secondly, rice production in Mazandaran province is strategic for the country. According to regional studies, the limited areas are appropriate for cultivating rice in Iran that means maximizing rice production in suitable regions is important for intensifying food security. Conversely, two major problems have been observed due to rice fields. First, high irrigation demand of the rice that makes it necessary to construct reservoir and water diversion structures. Available water at downstream river reach has been significantly decreased due to high water demand. Moreover, excess amount of nitrates would be drained into river due to runoff from rice fields. It should be noted that unsuitability of the aquatic river habitats might increase due to other source of water pollutant by urban source points and lack of sufficient instream flow. Hence, management of nitrate contamination as the main type of pollutant is necessary. Figure 7-1 displays river catchment location, land use and main structures. As a description on problem definition, Rajaei dam has been constructed at upstream of catchment due to proper location to regulate water demand at downstream. Moreover, given the appropriate outflow of tributaries after reservoir and conveying release water from dam, a water diversion structure has been constructed between location of dam and Sary city. In fact, most of available water would be diverted into agricultural lands in this area. On the other hand, runoff from rice fields flows into river at downstream of water diversion project. Thus, excess amount of nitrate damages aquatic habitat suitability at downstream of Tajan river due to lack of enough environmental flow. Hence, its management to recover river ecosystem at downstream is essential. The present chapter proposes a solution for this major problem by defining a flow regime from reservoir to reduce impacts of nitrate. Maximum storage of the reservoir is 160 MCM, minimum operational storage is 70 MCM and optimal storage in the reservoir is 140 MCM.

It should be noted that the department of environment has carried out extensive ecological studies in the river habitats of the study area. Based on the results and expert opinions, main generated pollutant by the rice fields is nitrate that might have significant impact on the river habitats. In fact, Nitrate is a serious threat for the native species that are inhabited at downstream river habitats. Hence, focus on nitrate concentration seems logical and justifiable in the present chapter. The safe nitrate concentration was defined in the study rea that was applied in the structure of the optimization model. In the Tajan river basin, the safe nitrate concentration was defined 20 mg/L. Defining threshold should be based on the environmental considerations in each river basin. In fact, threshold of nitrate might not be the same for all the aquatics. Hence, field studies might be needed. Field observations including fish observations and nitrate concentration measurements were carried out in the study area in different points. Based on the results, the number of fish will be considerable, if the concertation is less than 20 mg/L. Hence, considering SCF= 20 mg/L (SCF is safe level of Nitrate concentration) as the threshold in the optimization model is logical and defensible. We did not claim that this threshold is utilizable for all the river basins that means independent field studies might be needed in each river basins for determining SCF based on fish population in the habitats.

To sum up the problem in the study area, nitrate contamination from the rice fields needs to be managed robustly to mitigate the impacts on the aquatic habitats at downstream river. No regulated environmental flow is available in the current condition for minimizing the environmental impacts. Release from the reservoir should be able to mitigate the environmental impacts of the nitrate contamination. Hence, the reservoir operation of the Rajaei reservoir at upstream of Tajan river basin should be able to provide safe concentration of nitrate (i.e. 20mg/L) or less concentration in the simulated period. We selected 72 months as the simulation period in the basin in which nitrate concentration could be critical.

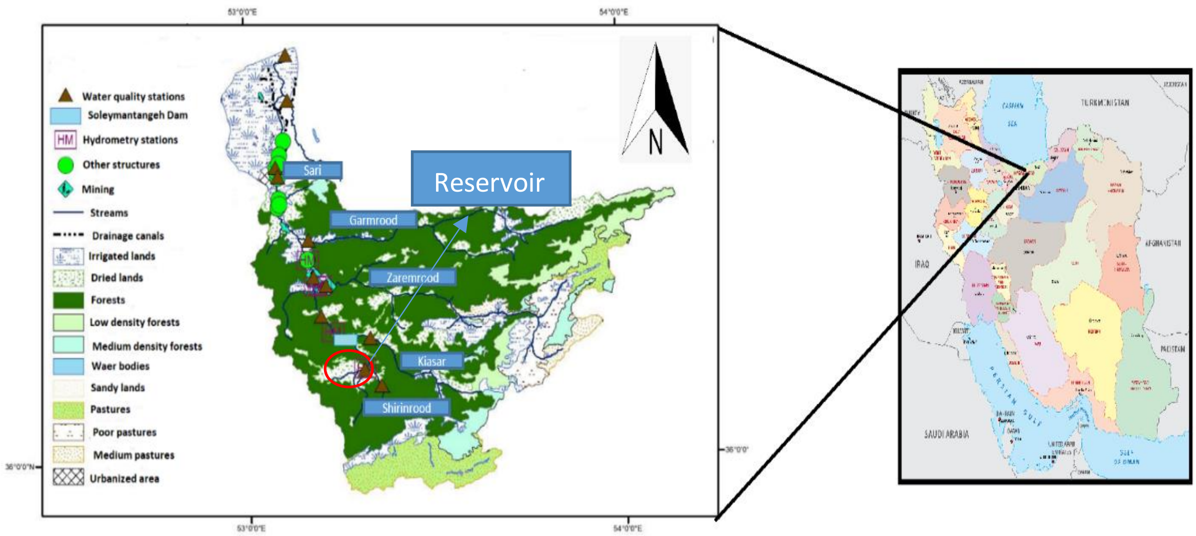



**Figure 7-1- Land use and river network map of Tajan basin**

### 7.2.3 Integrated hydrological modelling

We applied soil and water assessment tool (SWAT) as a robust river catchment model to simulate runoff and nitrate load. Figure 7-2 displays flowchart of SWAT methodology to simulate runoff and nitrate load. As can be seen, calibration and validation of SWAT results could be carried out by standalone program that has been named SWAT-CUP. Different inputs are needed to run SWAT in our case study.

Land use map was displayed in Figure 7-1 which reveals some points regarding Tajan river basin. Upstream lands where has been located at upstream of reservoir are mainly natural areas. In other words, there is least concern regarding nitrate due to croplands at upstream catchment. Furthermore, main cropland areas including rice fields have been located at downstream area of basin close to sea. In other words, downstream river ecosystem is seriously threatened by considerable load of nitrate. Hence, we assumed that total of nitrate load owing to crop would be occurred at downstream areas. Thus, main objective of optimization model is to mitigate impacts at downstream river ecosystem. Figure 7-3 displays digital elevation model (DEM) and slope map of Tajan river basin as other requirements for modelling by SWAT.

Due to complex processes in the SWAT to simulate flow and water quality, it is needed to present more details regarding the process. In the first step, watershed delineation is carried out in the GIS software environment by SWAT extension automatically. Next, surveyed land use map in the study area should be inserted to the model. It should be noted that only raster files are useable as the land use map in the modelling by SWAT. Soil map should be inserted to the model as well as land use map. It should be noted that it is required to insert the weather data before commencing simulation process. SWAT works based on the daily scale. However, outputs could be in the monthly scale. Thus, it is necessary to insert the weather data including daily air temperature and rainfall to the model. In the next step, SWAT applies hydrological unit method to compute flow and constituents concertation. Finally, user can commence simulation process by clicking on the simulation button. The outputs could be observed in the text file. However, the generated model is not useable before calibration and validation process.

It is necessary to review how the calibration by SWAT-CUP could be carried out. This standalone program is a tool for SWAT Calibration and Uncertainty analysis. One of the very applicable algorithms for calibrating results of SWAT in this program is Sequential Uncertainty Fitting (SUFI2) algorithm. SUFI-2 carries out a combined optimization and uncertainty analysis using a global search procedure. Many parameters could be considered in the runoff modelling. However, SWAT-CUP generally utilizes four calibration parameters including CN2.mgt (Initial SCS runoff curve number for moisture condition II), ALPHA_BF.gw(Alpha factor for groundwater recession curve of the deep aquifer(1/days)), GW_DELAY.gw (Ground water delay time) and GWQMN.gw (Threshold depth of water in the shallow aquifer required for return flow to occur (mm H2O)). In fact, SWAT-CUP is able to find the best values for the calibration parameters as mentioned to minimize the difference between observed stream flow and simulated stream flow.

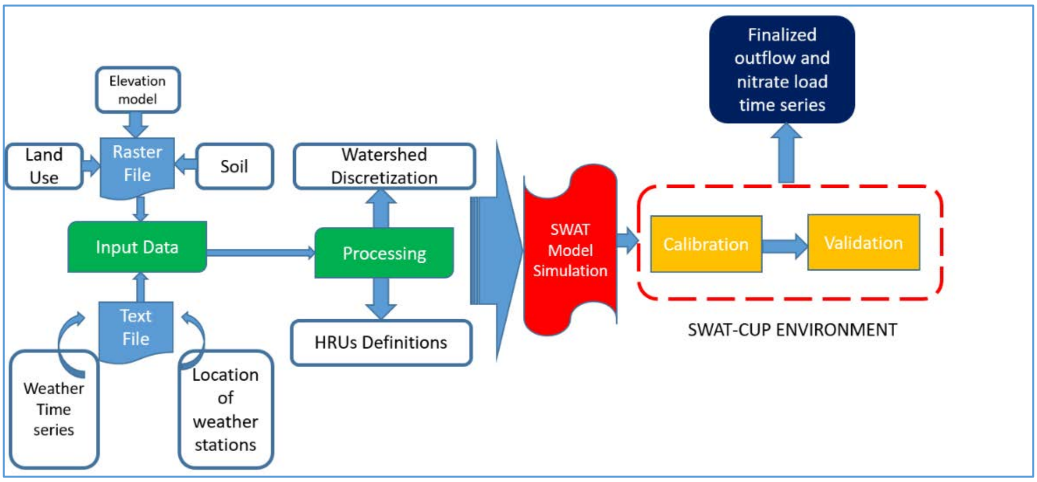
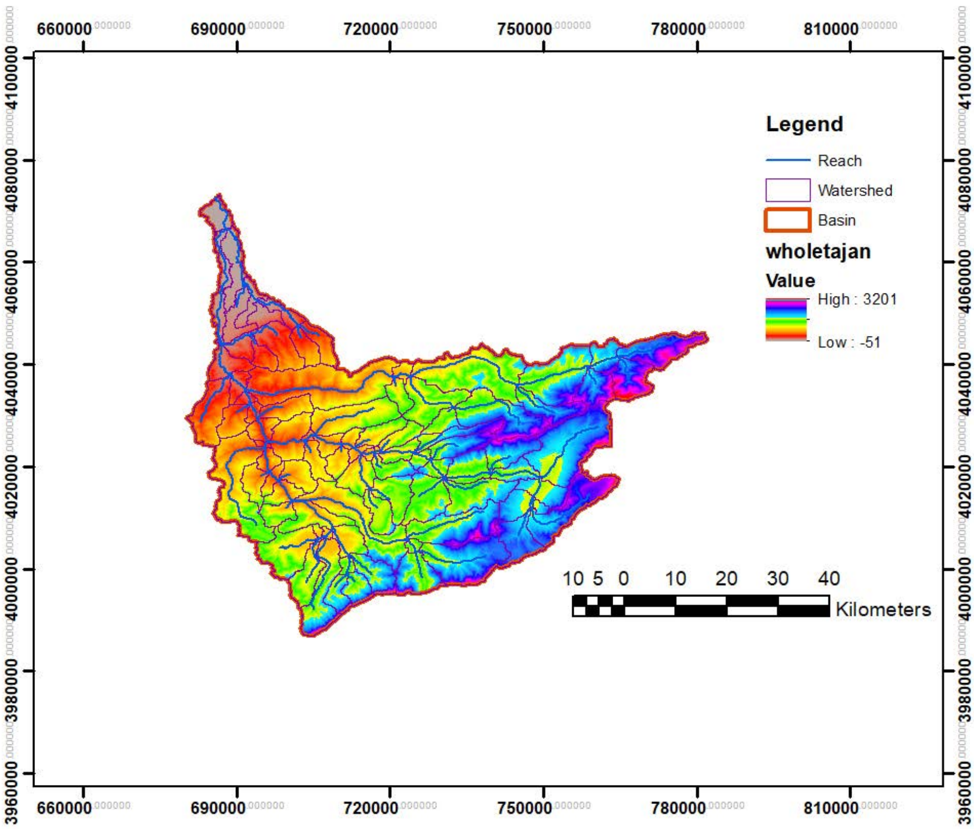



**Figure 7-2- Brief description of SWAT methodology**



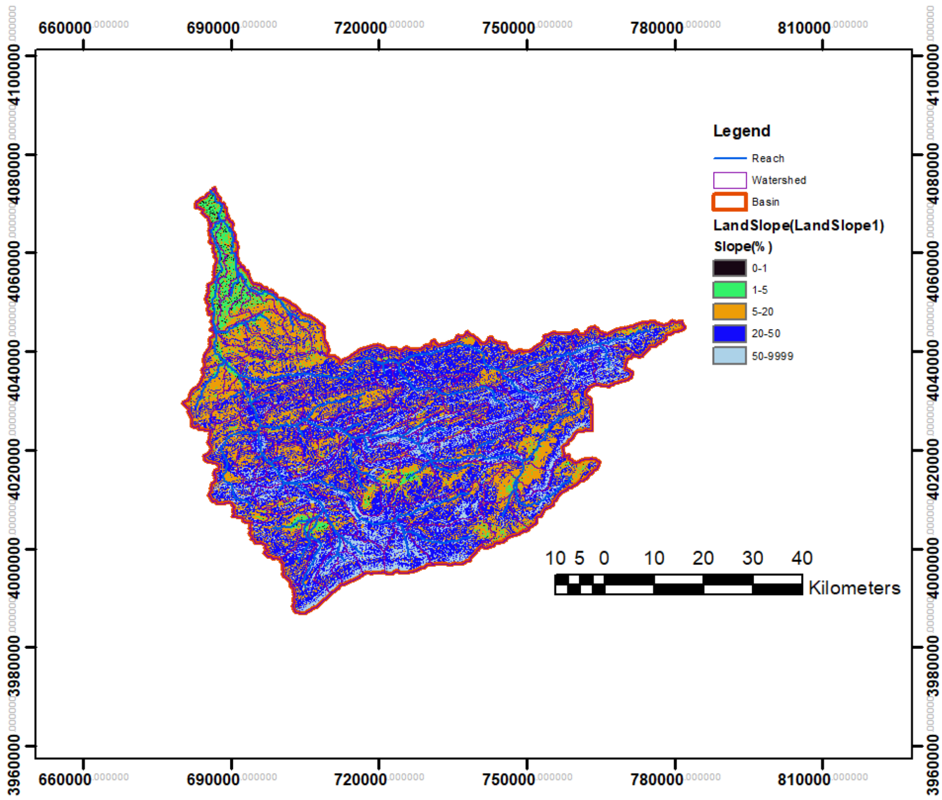



**Figure 7-3- Digital elevation model (Up) and Slope map (Down) of Tajan river basin**

### 7.2.4 Reservoir operation optimization

Defining objective function is the first step to develop reservoir operation model. Equation 1 displays defined objective function. This function contains two terms including water demand and nitrate concertation. Water demand term have been developed in the previous studies (Ehteram et.al, 2018a). However, second term is added in the present chapter.

$$OF = \sum_{t=1}^{T}\left(\frac{D_t - R_t}{D_t}\right)^2 + \left(\frac{SFC - NC_t}{SFC}\right)^2 \qquad (1)$$

where $D_t$ is demand, $R_t$ is release and $NC_t$ is nitrate concentration. SFC is safe nitrate concentration which does not make river habitats unsuitable. We considered SFC=20 mg/L in the present chapter. It should be noted that all of the consideration such as other pollutant sources were taken into account to define this value. Based on our investigation, this maximum concentration in the optimization model would protect habitats in terms of nitrate contamination. . In other words, this assumption assures us that released flow regime is reliable to protect downstream river habitats from possible damages to river ecosystem. Some constraints should be added based on considerations in reservoir management as follows

1-Storage constraints: Owing to importance of storage in the reservoir, we considered constraints regarding storage. In other words, storage benefits are dependent on storage level in the reservoir. Hence, minimum storage in the reservoir must be more than minimum operational storage. Moreover, storage must not be more than maximum possible storage in the reservoir. Thus, these two constraints were considered in optimization model.

2- Water demand constraint: release for water demand must not be more than requested water demand in each time step. Hence, it should be considered as another constraint in optimization model

3- Nitrate concentration constraint: It should be noted that objective function tries to minimize the difference between actual nitrate concentration and safe nitrate concentration. Obviously, nitrate concentration must not be more than safe nitrate concentration in the optimization model. Hence, a constraint is required in this regard.

Evolutionary algorithms were utilized to optimize reservoir operation. It should be noted that implementing the constraints in coded evolutionary algorithms might not be possible easily. Hence, using tricky solutions would be helpful in this regard. According to the literature, using penalty function method is a common procedure for reservoir operation optimization. In other words, this method is a known and popular method that has been used in many optimization cases such as reservoir optimization. Thus, we utilized penalty function method to convert a constrained optimization problem to unconstrained problem. Two penalty functions were added for storage as displayed in Equation 2. In fact, these penalty functions would increase penalty when storage is more than maximum storage or less than minimum operational storage. More details regarding the penalty function is available in the literature (Yeniay, Ö., 2005). Storage penalty function (equation 2) and water supply penalty function (equation 3) is originally proposed in the previous studies (e.g. Ehteram et.al, 2018a).

$$\begin{cases} if S_i > S_{max} \rightarrow P1 = c1\left(\frac{S_t - S_{max}}{S_{max}}\right)^2 \\ if S_i < S_{min} \rightarrow P2 = c2\left(\frac{S_t - S_{min}}{S_{min}}\right)^2 \end{cases} \tag{2}$$

Moreover, a penalty function is required for water demand as displayed in Equation 3. This penalty function would increase penalty when release for water demand is more than target demand.

$$if\ R_t > D_t \rightarrow P3 = c3\left(\frac{R_t - D_t}{D_t}\right)^2 \tag{3}$$

Final penalty function is related to nitrate concentration at downstream river reach. If nitrate concentration is more than safe concentration, penalty function will increase penalty for objective function as displayed in equation 4.

$$if\ NC_t > SFC \rightarrow P3 = c3\left(\frac{NC_t - SFC}{SFC}\right)^2 \tag{4}$$

Available water at downstream river reach (downstream of Sary diversion project) is very low. Hence, we considered it as zero in optimization model. In other words, we assumed no flow at downstream reach. Thus, new water allocation is required to mitigate impact of nitrate load from rice fields based on safe concentration at 20 mg/L. Furthermore, it is required to update storage in each time step by equation 5

$$S_{t+1} = S_t + I_t - R_t - EN_t - F_t - \left(\frac{E_t \times A_t}{1000}\right), t = 1,2,\ldots,T \tag{5}$$

where $S_t$ is storage at time period t, $I_t$ is inflow to reservoir at time t, $E_t$ is evaporation from reservoir surface at time t, A is area of reservoir surface, $R_t$ is release for demand in time period t, $EN_t$ is release for mitigating nitrate concentration and $F_t$ is overflow. T is the time horizon. Overflow would be computed by equation 6

$$\begin{cases} if\left(S_t + I_t - \left(\frac{E_t \times A_t}{1000}\right)\right) \geq S_{max} \rightarrow F_t = S_t + I_t - \left(\frac{E_t \times A_t}{1000}\right) - S_{max} \\ if\left(S_t + I_t - \left(\frac{E_t \times A_t}{1000}\right)\right) < S_{max} \rightarrow F_t = 0 \end{cases} \tag{6}$$

### 7.2.5 Evolutionary algorithms

Three evolutionary algorithms were used in the optimization process including differential evolution (DE), biogeography based optimization (BBO) and particle swarm optimization (PSO). Chapter 3 reviewed these algorithms.

### 7.2.6 System performance measurement

Each optimization model might need some indices to measure the performance of the model. In fact, these indices would measure how the model is able to cover the defined purposes for the optimization model. Some indices are known regarding the system performance analysis of the reservoir. For example, the reliability index is able to measure how the reservoir would supply water demand in the study area. Hashimoto et, al, 1982 suggested reliability index to measure reliability of water supply in a reservoir operation optimization. We used this index as displayed in equation 7. More details regarding the applicability of reliability index has been addressed in the literature (Yaseen et.al, 2019)

$$\alpha_R = \frac{\sum_{t=1}^{T} R_t}{\sum_{t=1}^{T} D_t} \tag{7}$$

Moreover, we applied mean absolute error (MAE) to measure robustness of optimization model in terms of supply of water demand and storage level as displayed in equation 8 and 9

$$MAE_R = \frac{\sum_{t=1}^{T} abs(R_t - D_t)}{T} \tag{8}$$

$$MAE_S = \frac{\sum_{t=1}^{T} abs(S_t - S_{opt})}{T} \tag{9}$$

Moreover, it was essential to measure system performance in terms of nitrate concentration mitigation. In other words, we should measure how impact of nitrate would be mitigated at downstream river ecosystem. Hence, failure index was defined in this regard as displayed in equation 10. This index indicates that in how many months nitrate concentration is more than safe concentration. FI is an improved form of resiliency index developed by Hashimoto et, al, 1982

$$FI = \frac{T_f}{T_S} \tag{10}$$

where $T_f$ is number of months in which nitrate concentration is more than safe concentration and $T_S$ is total number of simulated months. Furthermore, we simulated outflow of catchment and nitrate concentration by SWAT. Hence, it is required to measure robustness of inflow model. The Nash–Sutcliffe model efficiency coefficient (NSE) could be utilized to assess the predictive skill of SWAT as displayed in equation 1. More details regarding the NSE has been addressed in the literature (McCuen et.al, 2006)

$$NSE = \frac{\sum_{t=1}^{T} abs(Qm_t - Qo_t)}{\sum_{t=1}^{T} abs(Qo_t - MQo)} \tag{11}$$

$Qm_t$ is simulated outflow in time step t, $Qo_t$ is observed outflow in time step t and MQo is mean observed outflow. Similarly, this index would be used to measure robustness of model in terms of nitrate concertation.

### 7.2.7 Decision- making system

We applied fuzzy Technique for Order of Preference by Similarity to Ideal Solution (FTOPSIS) as decision-making system in the present chapter. It should be noted that using decision-making system would be essential when using different optimization algorithms are targeted. Figure 7-4 displays flowchart of FTOPSIS method to make a decision.

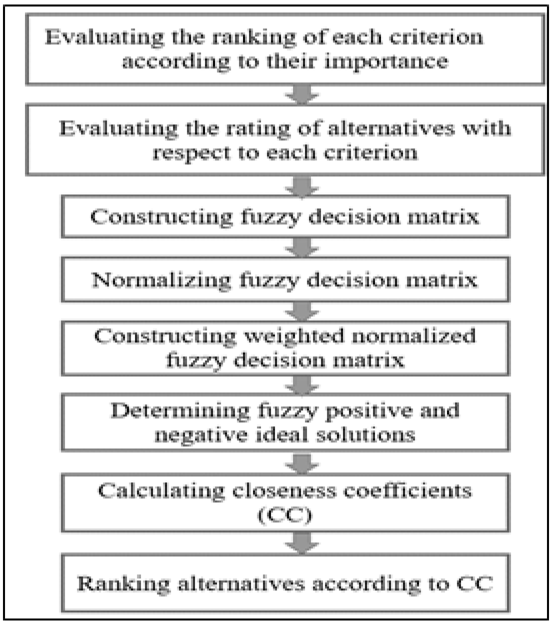
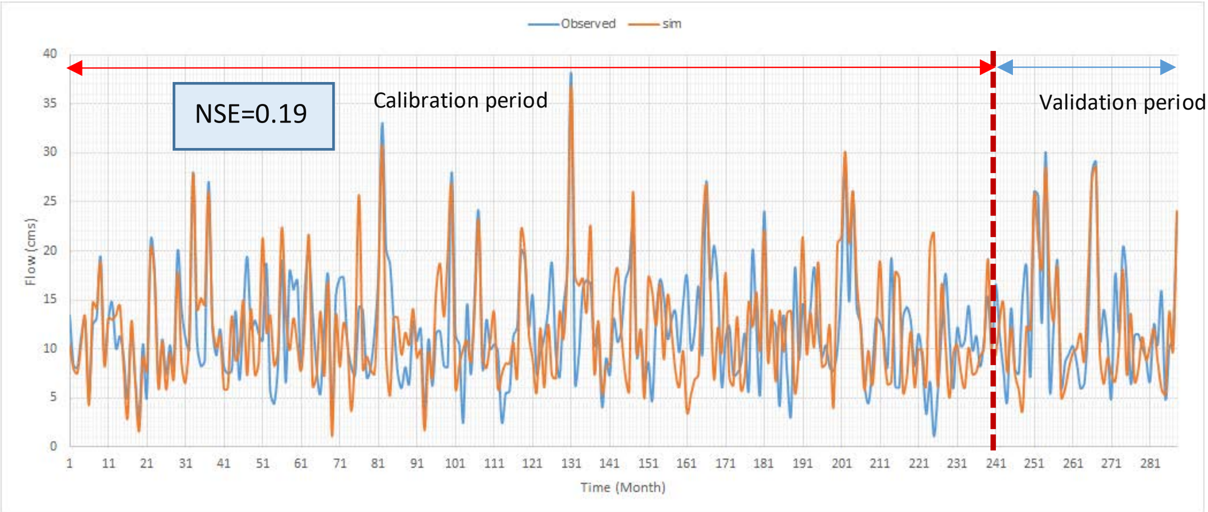
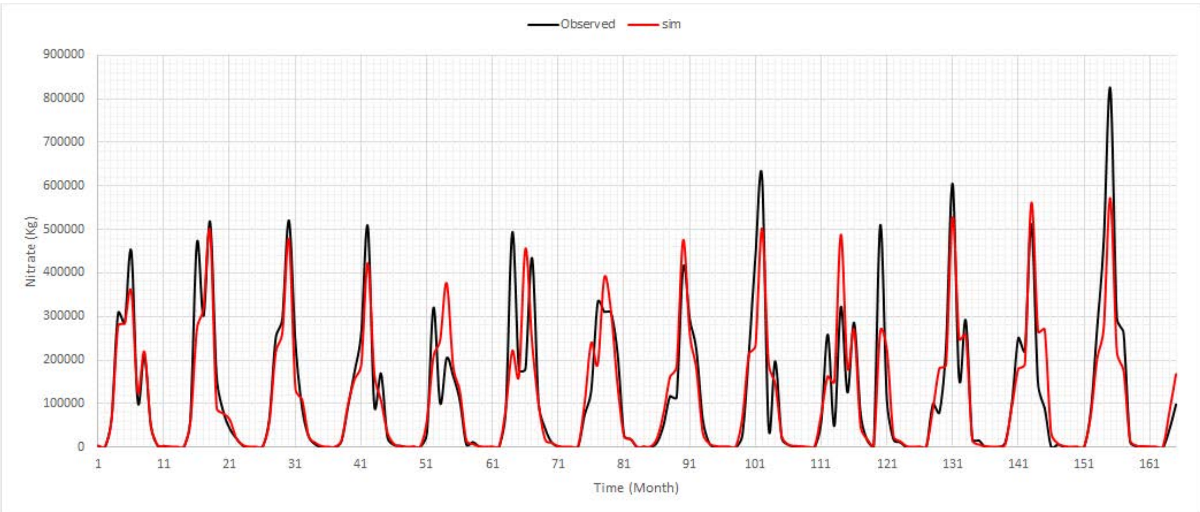


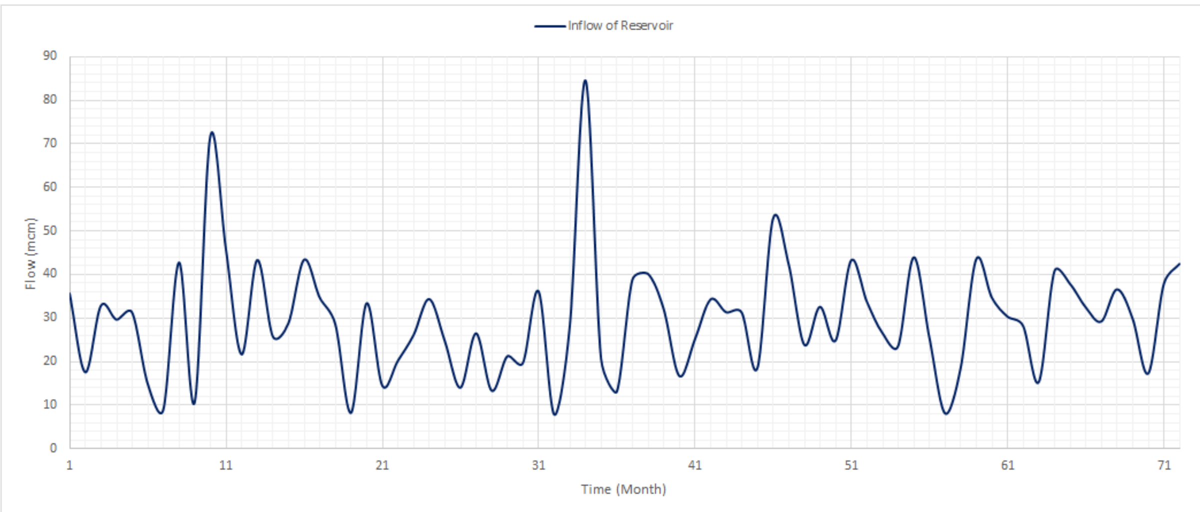

**Figure 7-4- Flowchart of fuzzy TOPSIS (Chen, 2000)**

## 7.3 Results and discussion

Figure 7-5 displays calibration and validation result of forecasting reservoir inflow that shows simulated monthly flow and recorded monthly flow. The most accurate model may have uncertainties that means the difference between model and observation would be expected in each modelling process. As discussed, we utilized NSE to measure robustness of forecasting flow model. Computed index is displayed on the Figures. Previous studies on application of NSE to evaluate hydrologic models demonstrated that $NSE = 0$ means that the model has the same predictive skill as the mean of the time-series in terms of the sum of the squared error. Previous studies by SWAT-CUP program to calibrate and validate outputs of SWAT indicate that NSE more than zero may be adopted as robust predictive skill for the model (Abbaspour et.al, 2015). Maximum NSE could be 1 that means complete match between model and observations. NSE for calibration and validation period is 0.19 that demonstrates acceptable predictive skill for developed model. According to the literature, if the NSE is more than 0.5, the model is robust and predictive skills are reliable. However, if the NSE is more than zero, the model might be averagely acceptable in terms of predictive skills. Hence, we could not claim that the model is robust to simulate flow. However, it is averagely acceptable. The previous studies corroborated that continuous hydrological simulation might be very complex and uncertainties might be considerable that is one of the limitations for continuous hydrological models. Previous studies corroborate the results of the present chapter and uncertainties in the continuous hydrological simulation. The calibration results demonstrated that the model is able to simulate peak points properly. Hence, final outputs of the model (optimization results) as the main finding of the study are almost reliable. . In other words, model is acceptably able to predict inflow of reservoir.



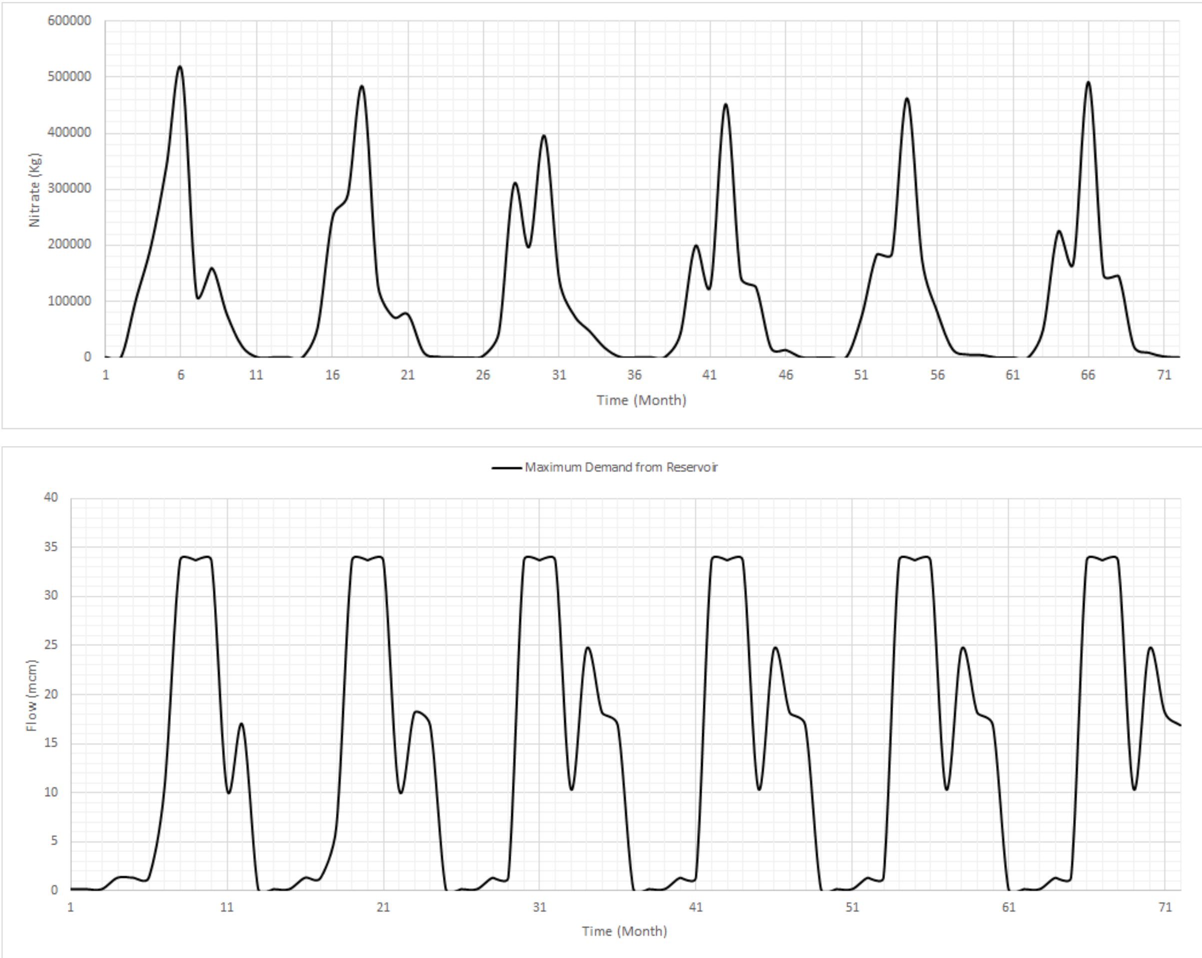



**Figure 7-5- Calibration and validation of outflow by SWAT (inflow to reservoir)**

Figure 7-6 displays calibration and validation results of nitrate concentration modelled by SWAT. It seems that model is robust in terms of prediction of nitrate concentration in simulated period. NSE is 0.74 that indicates model has strong predictive skills. It should be noted that calibration and validation of nitrate concentration was based on recorded water quality parameters in the past years when no dam or diversion project were constructed. In other words, they are nitrate load by cropland in recorded months.

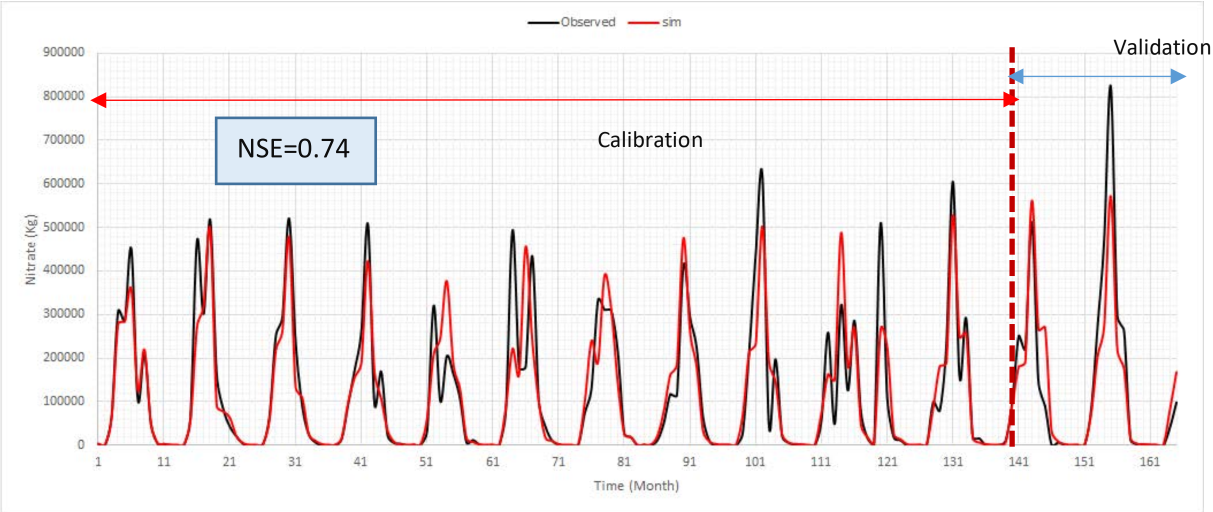



**Figure 7-6- Calibration and validation of nitrate concentration by SWAT**

Next step is computation of reservoir inflow in simulated period of reservoir operation. In other words, we considered 72 month as simulated period of reservoir operation to mitigate the impact of nitrate concentration at downstream river reach. Due to approved abilities of forecasting model, it is reliable to forecast inflow in an unrecorded period. Minimum reservoir inflow is less than 10 MCM. On the other hand maximum reservoir inflow is more than 80 MCM. Moreover, Figure 7-8 displays nitrate load by cropland during simulated period of reservoir operation. Nitrate load is remarkable in some months due to rice cultivation. Nitrate load damages river habitats considerably owing to very low flow after Sary diversion project. Figure 7-9 displays maximum requested water demand from reservoir. Comparing reservoir inflow and water demand indicates that reservoir has remarkable role to supply water demand.

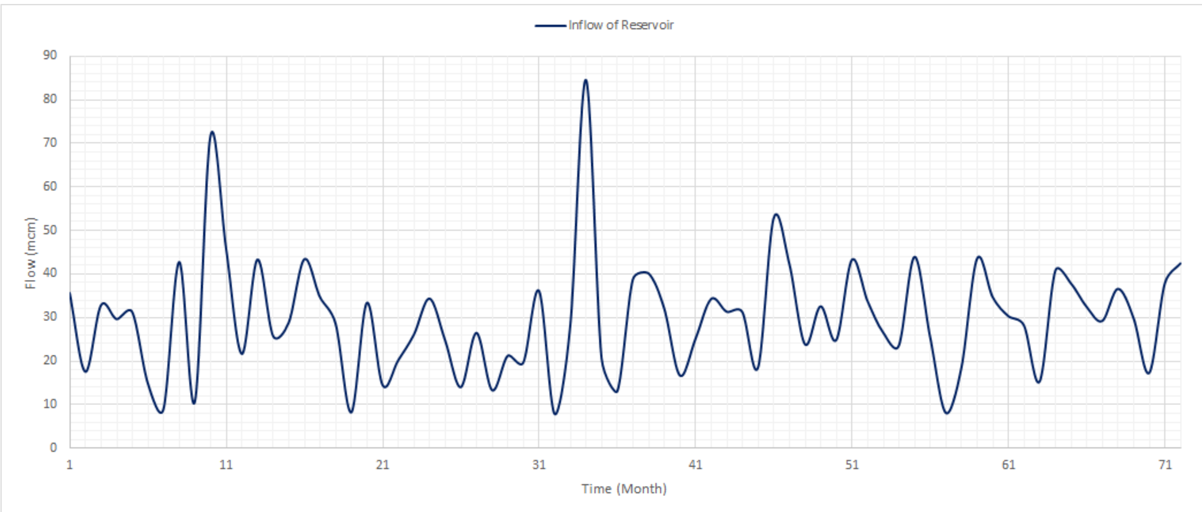



**Figure 7-7- Forecasting reservoir inflow during simulated period of reservoir operation**

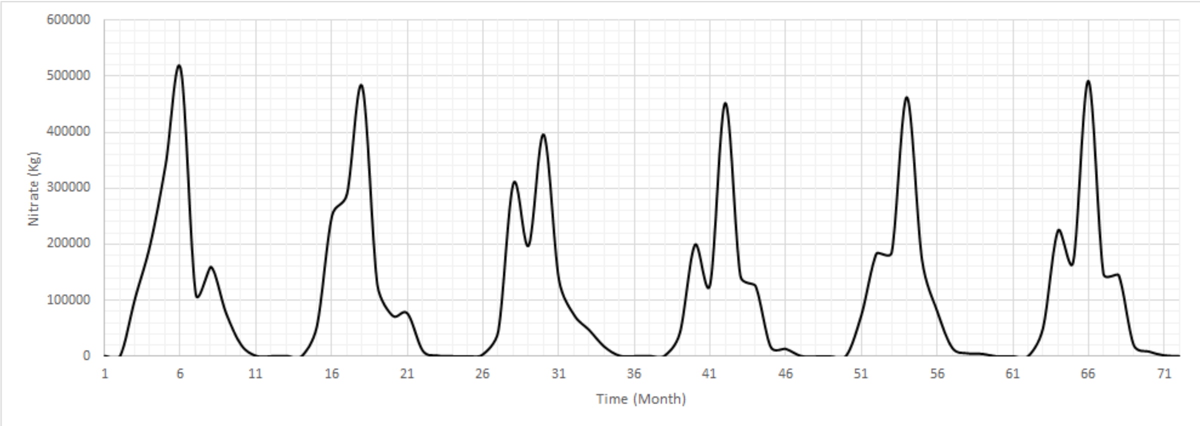



**Figure 7-8- Forecasting nitrate load by croplands during simulated period of reservoir operation**

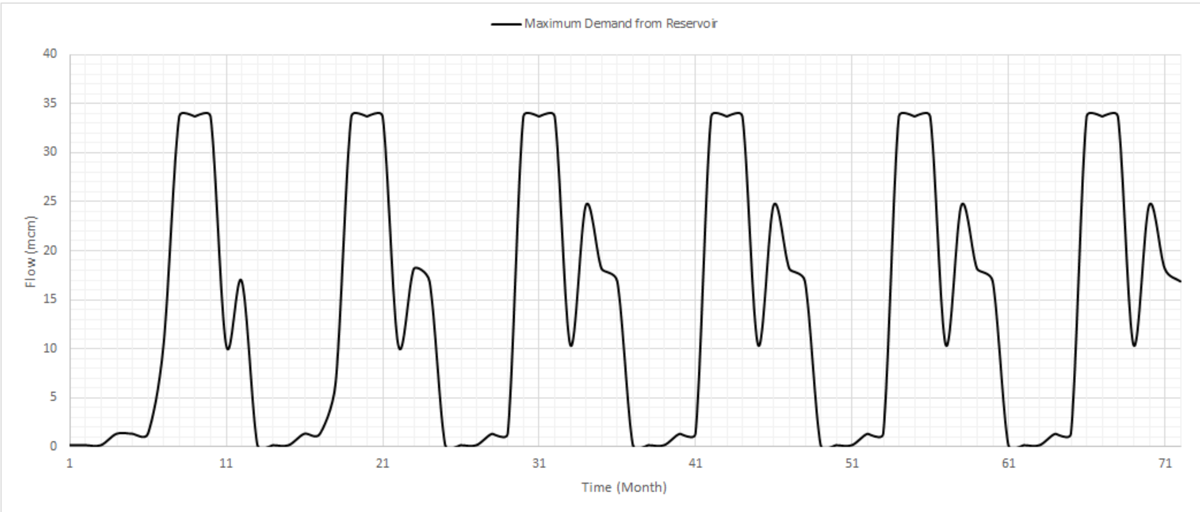



**Figure 7-9- Maximum water demand defined in optimization model**

Figure 7-10 displays results by differential evolution (DE) algorithm to optimize reservoir operation in terms of maximizing water supply, storage benefits and mitigation of nitrate concentration at downstream river ecosystem. Moreover, Figure 7-11 and 7-12 display results of BBO and PSO respectively. Nitrate concentration is displayed based on nitrate load in total released flow at downstream. It should be noted that it is not included release for water demand. Water demand is diverted before simulated segment. However, it includes release for environment and overflow. Release and storage time series indicate that performance of algorithms are different in terms of benefits. One of the aims in the optimization framework of present chapter was to reduce Nitrate concentration equal or less than 20 mg/L. It seems that performance of algorithms is not similar in this regard. Maximum Nitrate concentration by DE algorithm is 20 mg/L approximately. In contrast, maximum Nitrate concentration by PSO and BBO is higher than 20 mg/L. Maximum concentrations by BBO and PSO are approximately 35 and 40 mg/L respectively. However, considering maximum nitrate concentration is not enough to evaluate optimization method. In fact, reducing environmental impacts of nitrate is not the only purpose for the reservoir. In other words, an optimization method must be able to maximize all of the benefits of the reservoir simultaneously.

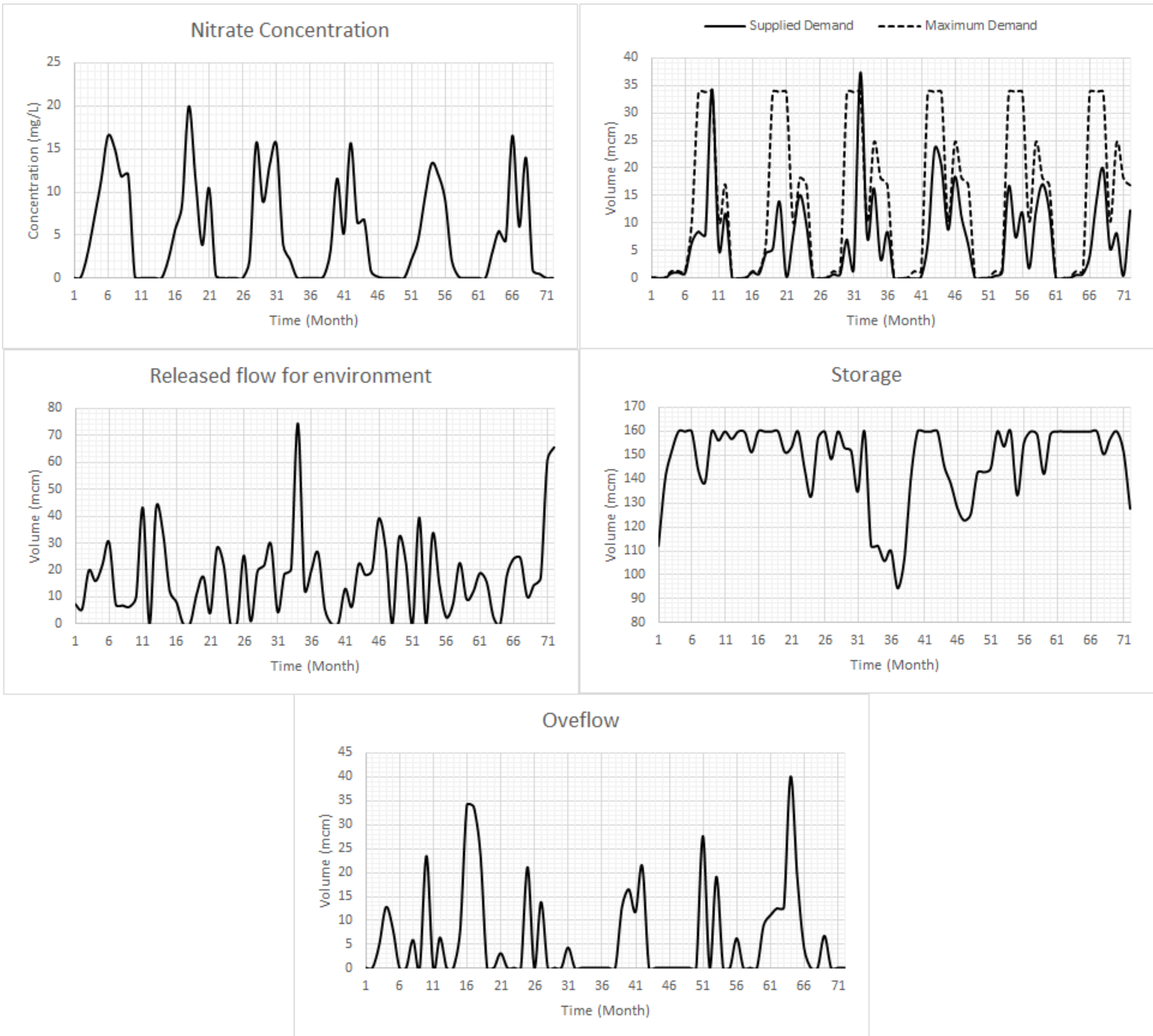



**Figure 7-10- Results of optimization by DE algorithm**

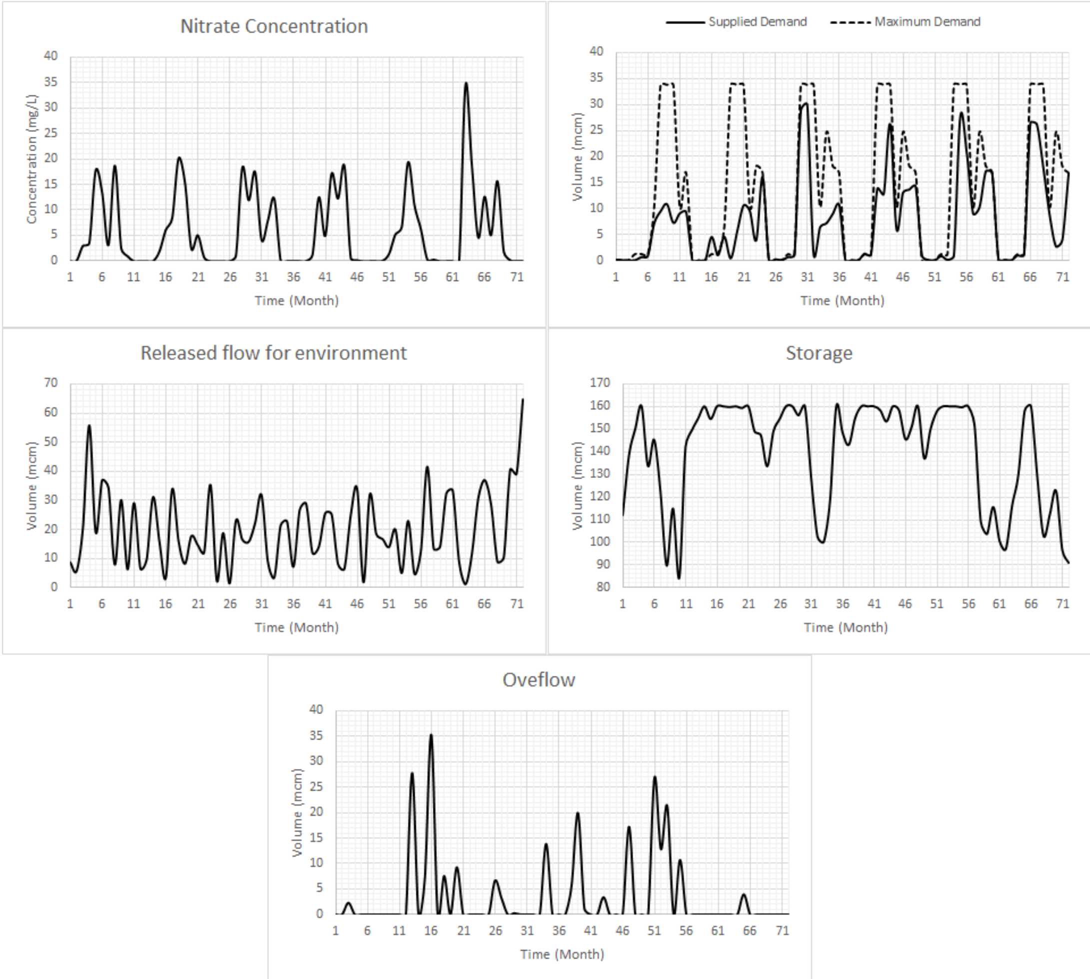



**Figure 7-11- Results of optimization by BBO**

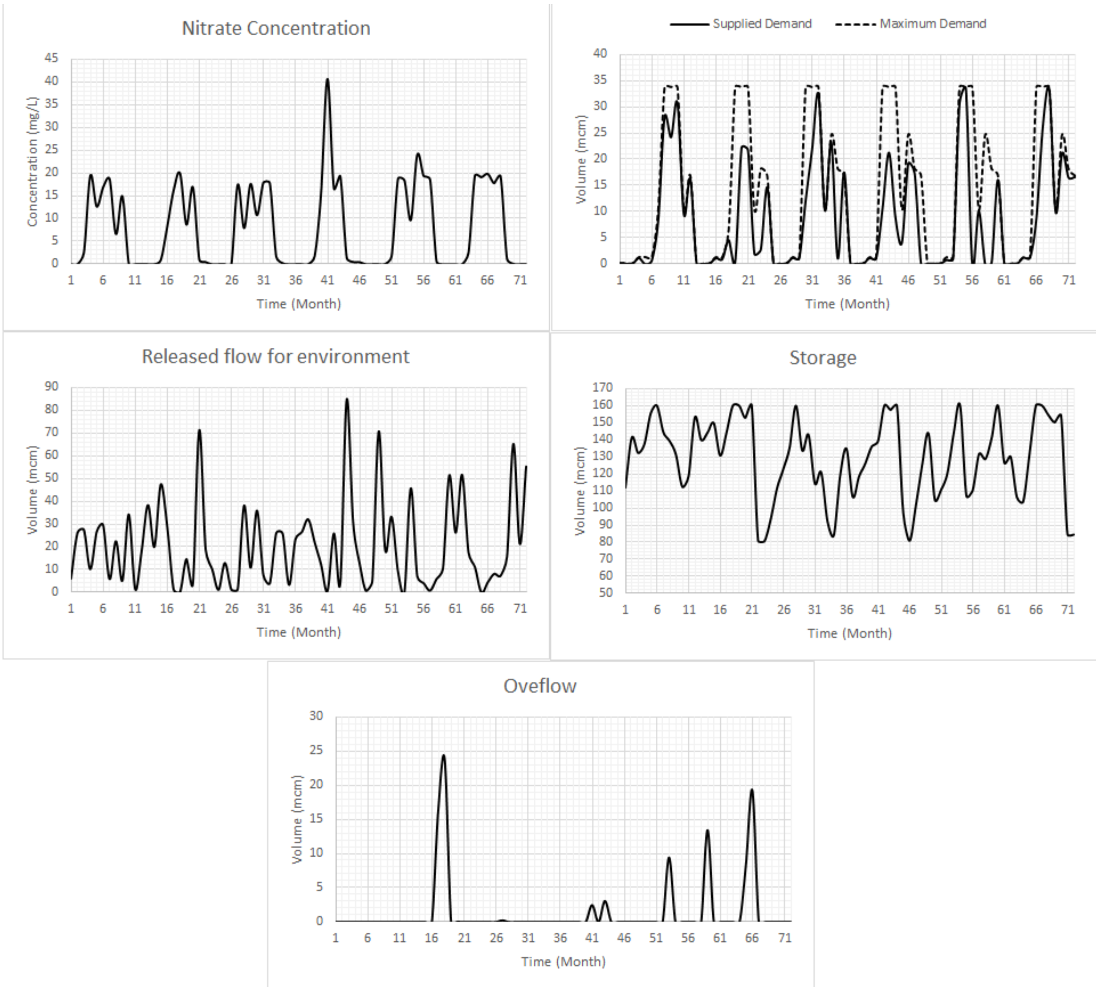



**Figure 7-12- Results of optimization by PSO**

For example, results by different algorithms demonstrate that their performance is different in terms of storage in the reservoir. Hence, using time series of storage, water demand and Nitrate concentration to compare and select the best algorithm is not possible directly. In other words, discussion on results need applying measurement indices as discussed in the previous section of the paper. We utilized reliability index and mean absolute error for water demand, mean absolute error for storage and failure index for Nitrate concentration. All of these criteria might be important to evaluate performance of optimization framework. We used two indices to evaluate performance of reservoir operation in terms of supply of water demand. The main purpose of construction of dam is supply of water demand. Hence, if it cannot have acceptable performance in terms of water supply it might not be assessed as suitable optimization model. However, other criteria including storage measurement index and failure index of Nitrate are important as well. Reliability index of water supply indicates that PSO is the best algorithm. This algorithm is able to supply more than 60% of maximum water demand. However, DE as the weakest method is not able to supply more than 45% of maximum demand. It should be noted that 15% difference

between the weakest and the best algorithm could be considerable in practical reservoir operation. MAE for demand is a good criterion to evaluate performance of algorithms in terms of errors to supply water demand in simulating period. It should be noted that this index is the cost for the optimization system unlike reliability index that is a benefit. In other words, optimization system should minimize MAE for demand. Based on Figure 7-13, PSO is the best method in terms of MAE. Hence, it could be concluded that PSO is the best algorithm to supply water demand at downstream of reservoir. However, it is required to measure performance of algorithms in terms of storage and Nitrate concentration.
It should be noted that reliability index is not an appropriate index to measure performance of model in terms of storage. In fact, summation of storage benefits is meaningless. Hence, using MAE for storage could demonstrate performance of model regarding storage by displaying mean error compared with optimal storage. MAE for storage is also the cost index for the system. Thus, its minimization is favorite. DE is the best method to minimize storage loss in the reservoir. Performance of either BBO or PSO is not as robust as DE. However, BBO is more robust compared with PSO. It seems that results by different algorithms are contradictory. PSO is the best method to supply water demand though it is not robust method to maximize storage benefits.

FI is the last index to measure system performance in terms of Nitrate concentration. This index is the cost for the system. If it increases, the performance of the system will be weakened. DE is the best method in this regard. In other words, this algorithm minimizes number of failures. Performance of PSO and BBO is the same regarding Number of failures. Performance of optimization model to maximize benefits of the reservoir is complex due to contradictory results. Hence, it is not possible to select the best algorithm easily. It sounds that it is necessary to use a robust decision-making system to select the best solution. As presented in the previous section, we used FTOPSIS method to make a decision regarding algorithms. Two main requirements for applying FTOPSIS method is estimation of weight of importance and rating of alternatives or candidates. Table 7-1 displays weight of importance. We considered H(high) for reliability index and MAE of water demand. Furthermore, weight of importance for error of storage and failure index were considered as very high (VH). In fact, we utilized two indices for water demand and one index for storage or Nitrate concentration. Thus, considering high for water demand indices and very high for other two indices is seemingly logic.

**Table 7-1- Weight of importance**

| | Reliability index (demand) | MAE(demand) | MAE(storage) | Failure Index |
|---|---|---|---|---|
| Weight of importance | H | H | VH | VH |


**Figure 7-13- Results of calculating measurement indices**

Another requirement for using FTOPSIS method is rating of alternatives. Table 7-2 shows rating of alternatives in the present chapter. We discussed regarding performance of alternatives. Hence, rating process was carried out based on performance of algorithms. In Table 7-2, VG, G, F and RP mean very good, good, fair and relatively poor respectively. It should be noted that type of criteria has been considered in rating which means each criterion might be cost or benefit as discussed.

**Table 7-2- Rating of alternatives**

| | Reliability index (demand) | MAE(demand) | MAE(storage) | Failure Index |
|---|---|---|---|---|
| PSO | VG | F | VG | G |
| BBO | G | G | G | G |
| DE | F | VG | F | RP |

**Table 7-3- Results of computing D+ and D-**

| | D+ | D- |
|---|---|---|
| PSO | 0.22 | 0.86 |
| BBO | 0.31 | 0.8 |
| DE | 0.58 | 0.5 |

Table 7-3 shows result of computing D+ and D- by FTOPSIS method. These values were utilized to calculate closeness coefficient (CC) to prioritize methods. If CC is higher for a method, it will indicate that method is more suitable to optimize reservoir operation by proposed framework in the present chapter. Figure 7-14 displays final ranking by FTOPSIS method. Based on ranking, PSO is the best method to optimize reservoir operation. This output needs a discussion on outcome of present chapter and some points must be noted that for further application of proposed optimization framework. The initial purpose of proposed framework was defined based on mitigation of Nitrate concentration at downstream of the reservoir. However, other benefits of the reservoir including storage benefit and supply of water demand were considered in the context of optimization. Results demonstrate that outcome of optimization model might be complex. In other words, not all of the expected achievement could be seen in outputs. DE is a good method in terms of reducing Nitrate concentration. It is able to consider defined safe concentration. However, it is not able to maximize benefits of water supply at downstream. Conversely, PSO is a proper option to maximize water supply benefits. However, it is not very robust method to minimize Nitrate concertation impacts based on defined safe concentration compared with DE algorithm. It seems that using reservoir to control water quality at downstream might not be useable easily which means it is essential to minimize all of the losses simultaneously. In other words, using decision-making system is necessary in reservoir operation optimization when complex impacts such as control of downstream water quality would come to picture. Using robust measurement indices is another recommendation by the present chapter. If we do not utilize measurement indices in all of the aspects of reservoir benefits, it will create misconception regarding reservoir operation. In other words, it is possible to select incorrect optimization solution for reservoir operation.

A full discussion regarding different aspects of the proposed method is essential. First, it is essential to discuss on results in terms of environmental issues by highlighting causes and effects. Moreover, each optimization system might have some advantages and limitations that should be noticed in the applications. The results of the present chapter demonstrated that reservoir could be an environmental tool to mitigate impacts of human activities such as agriculture on the aquatic habitats while it would be able to carry out defined responsibilities such as water supply. The main effect of using reservoir for reducing the environmental impacts was to mitigate nitrate concertation in most of the time steps. However, its performance might not be perfect in all the time steps. The high nitrate concentration considerably detrimental for the aquatic habitats in terms of all biological activities. In our field studies, we focused on the fish species in the Tajan River. The main environmental impact of high nitrate concentration is to decrease the population of fish in the river that might be deleterious for the river ecosystem. It is important to discuss how nitrate contamination could be effective on the population. In fact, high nitrate concentration reduces the reproduction by the adult fishes because suitable habitats are not available. Moreover, high nitrate concentration might perish the juvenile fish. It might be intensified when concentration in most of the time steps is higher than defined threshold as the safe level. Using the proposed optimization method diminish the possibility of perishing juvenile fish in the Tajan River habitats. Another important point that should be discussed is weight of importance for different factors as displayed in the table 7-1. Selecting the weight of importance should be based on the environmental considerations in the case study. In the present chapter, environmental impacts are important. Hence, failure index was taken into account as very high. However, other responsibilities of reservoir such as water supply have been considered as high. Hence, weight of importance might have considerable impact on selecting the best algorithms and related environmental impacts in the river. Some limitations should be noted regarding the proposed method. First, using SWAT needs adequate recorded flow and water quality data. Hence, if enough recorded data is not available, the proposed method might not be applicable that is the main limitation of the proposed method. Moreover, simulating a long-term period might increase the computational complexities. Thus, using the proposed method for very long-term period might need significant computational time. Furthermore, the propose method should be improved when point and non-point source of pollution are available in the study area simultaneously. To sum up, some points should be noted as outcome of the present chapter as follows

Reservoir could be utilized as a reliable tool to reduce environmental impacts of Nitrate load at downstream by application of an optimization framework. It should be noted that increasing population makes it essential to expand farms such as rice fields to supply food demand. Hence, using reservoirs as tool to reduce environmental impacts would be beneficial. These expensive structures have been constructed to supply water or electricity demand. Thus, using reservoirs for mitigation of environmental impacts is a benefit for these hydraulic structures.

The reservoirs are generally multipurpose. Hence, optimization framework must be defined to maximize all of the benefits of the reservoir. In the present chapter, three main purposes were considered including storage benefit, water supply benefit and mitigation of environmental impact of Nitrate load. Using three optimization algorithms including DE, PSO and BBO demonstrated that using different algorithms is essential in practical projects. Outputs might be contradictory. In other words, an algorithm might have good results in terms of one of the benefits though other algorithms might have weak performance. It should be noted we could not judge regarding performance of algorithm by the observation. It is required to use a quantified system to make a decision. Using decision-making system needs two requirements. First, applying robust measurement indices as criteria in the decision-making system. Secondly, considering all of the benefits in decision-making system. We considered three reservoir benefits including water supply, storage benefits and mitigation of Nitrate impacts in our decision-making system. It seems that it is essential to consider these three main purposes in similar studies at least. Outcome of decision-making system might not fully support initial objectives of optimization model. However, it is the best available output due to existent condition. In other words, it is able to minimize all of the losses for the reservoir operation optimization.

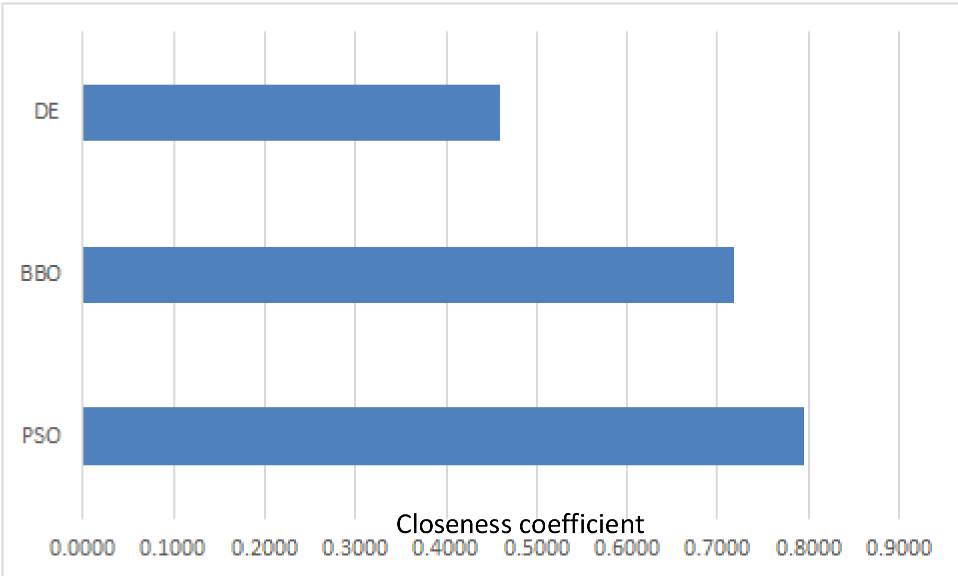



**Figure 7-14- Final ranking by FTOPSIS method**

## 7.4 Summary

The present chapter proposes a multipurpose reservoir operation optimization for mitigating impact of rice fields' contamination on the downstream river ecosystem. The developed model was applied in the Tajan river basin in Mazandaran province, Iran in which the rice is the main crop. We used soil and water assessment tool (SWAT) to simulate inflow of the reservoir and nitrate load at downstream river reach. Nash–Sutcliffe model efficiency coefficient was used to measure the robustness of SWAT. NSE indicated that SWAT is acceptable to simulate nitrate load of the rice fields. The results of SWAT was applied in the structure of a multipurpose reservoir operation optimization in which three evolutionary algorithms including differential evolution algorithm, particle swarm optimization and biogeography based algorithm were utilized in the optimization process. Reliability index, mean absolute error and failure index were used to measure the robustness of the optimization algorithms. Fuzzy Technique for Order of Preference by Similarity to Ideal Solution was utilized to select the best algorithm. Based on results, particle swarm optimization is the best method to optimize reservoir operation in the case study. The reliability index and mean absolute error for water supply are 0.6 and 5 million cubic meters respectively. Furthermore, the failure index of contamination is 0.027. Hence, it could be concluded that the proposed optimization system is reliable and robust to mitigate losses and nitrate contamination simultaneously. However, its performance is not perfect for minimizing impact of contamination in all the simulated months.

## Chapter 8: Environmental operation of reservoirs considering environmental flow

Full contents of this chapter have been published and copyrighted, as outlined below:

Sedighkia, M., Datta, B. and Abdoli, A., 2021. Optimizing reservoir operation to avoid downstream physical habitat loss using coupled ANFIS-evolutionary model. Earth Science Informatics, 14(4), pp.2203-2220.

Sedighkia, M. and Datta, B., 2022. A simulation-optimization system for evaluating flood management and environmental flow supply by reservoirs. Natural Hazards, 111(3), pp.2855-2879.

Sedighkia, M., Datta, B. and Abdoli, A., 2021. Design of optimal environmental flow regime at downstream of reservoirs using wetted perimeter-optimization method. Journal of Hydro-environment Research, 39, pp.1-14.

Sedighkia, M. and Abdoli, A., 2022. Design of optimal environmental flow regime at downstream of multireservoir systems by a coupled SWAT-reservoir operation optimization method. Environment, Development and Sustainability, pp.1-21.

Sedighkia, M., Datta, B. and Fathi, Z., 2022. Linking ecohydraulic simulation and optimization system for mitigating economic and environmental losses of reservoirs. AQUA—Water Infrastructure, Ecosystems and Society, 71(2), pp.229-247.

Sedighkia, M., Datta, B. and Abdoli, A., 2022. Reducing the conflict of interest in the optimal operation of reservoirs by linking mesohabitat hydraulic modeling and evolutionary optimization. Water Supply, 22(2), pp.2269-2286.

### 8.1 Introduction

The large dams are expensive hydraulic structures that might have significant role for development of the communities (Altinbilek, 2002). Optimal reservoir operation is a critical task to maximize benefits of the large dams. Hence, optimization of the reservoir operation has been highlighted in the literature. Two main aspects are important in the reservoir operation optimization including optimization method and objective function. The linear programming (LP) was the simplest method to optimize reservoir operation (Yeh, 1985). Due to non-linearity of the reservoir operation, non-linear programming (NLP) and dynamic programming (DP) were proposed for the reservoir operation optimization (e.g Birhanu et.al, 2014; Zhao et.al, 2014). Complexities of the objective function made it necessary to utilize other methods for increasing the efficiency of the optimization. Thus, evolutionary algorithms have been proposed to improve the optimization process of the reservoir operation in recent decades. These algorithms are classified in two groups including animal and non-animal inspired evolutionary algorithms (Jahandideh-Tehrani et.al, 2019). Animal inspired algorithms imitate social behaviours of the animals such as bat algorithm (Yang and He, 2013). In contrast, non-animal inspired algorithms are motivated by other natural phenomena or laws. For example, the gravity search algorithm has been inspired by the gravity law (Rashedi et.al, 2009). Evolutionary algorithms might be classified as the classic and new generation algorithms as well (Dokeroglu et.al, 2019). The best examples of the classic algorithms are the genetic algorithm (GA) and the particle swarm optimization (PSO) (Chen and Chang, 2007; SaberChenari et.al, 2016). Using different evolutionary algorithms for the reservoir operation seems essential. In fact, the objective function of the reservoir operation is a complex function that means evolutionary algorithms might not guarantee the global optimization. Hence, a wide range of the classic and new generation algorithms have been utilized to optimize reservoir operation (e.g Afshar et.al, 2007; Haddad et.al, 2016; Asgari et.al, 2016; Haddad et.al, 2015a; Haddad et.al, 2015b; Afshar et.al, 2011; Yaseen et.al, 2019).

It is essential to review the recent improvements for using evolutionary algorithms in the water resource management and the reservoir operation. Applicable methods for optimizing the operation of the multireservoir systems using evolutionary algorithms and application of neural networks and fuzzy rule-based systems for inferring reservoir system operating rules have been reviewed in the literature (e.g Labadie, 2004). Different evolutionary algorithms have been highlighted in the previous studies. For example, it is demonstrated that the fully constrained particle swarm optimization might be advantageous for optimizing reservoir operation (Afshar, 2012). Optimizing hedging rules for operating reservoir systems is another application of the particle swarm optimization (PSO) in optimal management of the reservoirs. For instance, two phases method that combines PSO with the simulation of the water system was used to mitigate the drought impacts by optimizing hedging rules of the reservoir operation (Spiliotis et.al, 2016). Improving the performance of the multi-objective genetic algorithm is one of the important improvements in the application of the genetic algorithm (Guariso et.al 2020). Moreover, the simulated annealing algorithm has been applied in the hybrid mode such as hybrid cellular automata-simulated annealing to optimize the reservoir operation and hydropower operation of the multireservoir systems (Teegavarapu and Simonovic, 2002; Azizipour et.al, 2020). Ant colony is another robust algorithm utilized in the water resource problems (e.g Maier et.al, 2003). Stochastic approaches are significant improvement for optimizing the reservoir operation (e.g Guariso and Sangiorgio, 2020; Sangiorgio and Guariso, 2018).

As presented, another important aspect in the reservoir operation optimization is how to define objective function and constraints. A principal form of the loss function has been defined to minimize the difference between release and target in the reservoir operation (Hashimoto et.al, 1982). Moreover, it is highlighted that storage loss should be considered in the optimization system (Datta and Burges, 1984). This type of optimization model has been used in many recent studies (e.g Ehteram et.al, 2018). If supply of electricity is a purpose for the reservoir, optimization model might be defined based on maximizing supply of the electricity (Cheng et.al, 2008). Environmental aspects in the river basin management have been highlighted in recent decades. Thus, it should be added to the reservoir operation systems. Environmental impacts at upstream and downstream might be important in the management of the reservoir. Environmental impacts have rarely been addressed in the reservoir operation (e.g Yin et.al, 2012). However, the previous studies highlighted the importance of the integrated system for water resource management. For example, the multi-objective decisions support system for integrating physical, biological, economic and social processes in the optimization of the water resource systems has been introduced in the literature (Soncini-Sessa et.al, 2007). The downstream environmental impacts are highlighted in the present chapter.

Degradation of the aquatic habitats at downstream of the dams is a serious concern. Thus, the concept of environmental flow regime has been defined to protect suitability of the downstream river habitats. Many methods have been developed to assess environmental flow regime including hydrological methods, hydraulic rating methods, physical habitat simulation methods and holistic methods (Tharme, 2003). Ecological based methods are reliable due to focus on the regional ecological values. Due to importance of environmental flow optimization, some previous studies proposed the optimization of environmental flow for the reservoirs (e.g Cai et.al, 2013; Horne et.al, 2017). However, considering environmental flow in the optimization model might be challenging in terms of two aspects. First, defining environmental flow regime in the optimization model might be a complex task. Many methods might be available to define environmental flow regime. Secondly, integrated optimization model is required. In other words, it is necessary to integrate water supply loss and environmental impacts. It seems that engineers face a complex problem for optimizing environmental flow regime in the reservoirs. Thus, more studies are essential in this regard. One of the requirements for optimizing environmental flow is to utilize reliable models to forecast inflow due to its considerable effect on the release.

Two main methods have been proposed to forecast inflow of the reservoirs including hydrological modelling of the upstream catchment and data-driven models such as neural networks (Maier et.al, 2000). Neural networks might not be reliable in all the cases. They need rich data bank for training and testing process that might not be available in all the cases. In contrast, hydrological models might need less data for calibration and validation. More details regarding advantages and disadvantages of the data-driven models have been addressed in the literature (Dumitru and Maria, 2013). Continuous hydrologic simulation is one of the important recent recommendations to enhance the accuracy of the river flow or flood assessment (Ball et.al, 2016). Soil and water assessment tool (SWAT) is a robust continuous hydrologic simulation model that has extensively been cited in the literature to simulate outflow of the catchments (e.g Gassman et.al, 2007; Neitsch et.al, 2009). This chapter develops several simulation-optimization frameworks for adding environmental flow model to the reservoir operation optimization in which several methods have been applied in assessing environmental flow.

Main contribution of section 8.1 is to propose a flexible framework to use wetted perimeter method as an applicable environmental flow assessment method to assess optimal environmental flow regime considering water supply and storage constraints in the reservoir. Moreover, system performance has been measured by different indices. Due to using different optimization algorithms in this research work, a decision-making system was applied to rank optimization methods. Proposed simulation-optimization method was utilized in a case study to test robustness of the method. This method might be useable to optimize environmental flow regime at downstream of reservoirs for reducing conflict between water demand and environmental requirements that is able to consider storage constraints as well.

The section 8.2 develops a framework to minimize physical habitat loss for the downstream aquatics of the reservoirs considering fixed water demand and storage constraints in the reservoir management. In other words, we linked ANFIS based physical habitat model and an evolutionary optimization to assess optimal release from the reservoir in which physical habitat simulation is applied to assess physical habitat loss. The developed optimization system is able to minimize environmental impacts at downstream of the reservoirs in terms of physical habitat suitability. The most important advantage of the proposed method is to apply an integrated optimization system that is able to optimize the storage loss and the physical habitat loss simultaneously. Utilizing the proposed framework might reduce negotiations between reservoir managers and environmental advocators. In fact, the proposed method is able to provide an optimal environmental flow. Other environmental and technical considerations might be added to the proposed system in the future researches to improve the applicability of this method.

The section 8.3 proposes and evaluates a novel framework to mitigate environmental impact of the reservoirs at downstream river habitats by a linked mesohabitat modelling- optimization method. One of the most important impacts of the reservoir is reduction of river flow that might directly affect the Pool/Riffle sequences. Changing pool, run and riffle area might reduce habitat suitability at downstream river reach due to specific role of each mesohabitat unit for the biological activities of the aquatics such as fish. Hence, one of the effective methods for mitigating downstream environmental impact of reservoirs could be minimization of the difference between area of mesohabitat units in the natural status and the optimal status. However, the proposed reservoir operation model must be able to maximize benefits from the reservoir. The proposed method in this research work is applicable for cases in which downstream environmental impact of reservoir is a serious concern and different species could be observed at downstream river reach. In fact, existence of different species indicates that using target species based ecological environmental methods such as physical habitat simulation might not be able to protect all the species. Using mesohabitat modelling method is generally able to maximize habitat suitability for all the species. Hence, it would be one of the proper methods to mitigate downstream environmental impacts of reservoirs.

The section 8.4 proposes an integrated simulation-optimization system in which the flood hazards or possible flood damages and downstream environmental impacts are minimized while other benefits form the reservoir including water supply is maximized. The proposed framework opens new windows regarding the integrated management of the multipurpose reservoirs. Two aspects should be noted in the application of the proposed framework including assessment of the reservoir operation in the past periods to recognize drawbacks in the reservoir management and simulation of the future periods by the linked forecasting river flow, climate change and reservoir operation models.

The section 8.5 proposes a simulation-optimization framework to design optimal environmental flow regime downstream of the multireservoir systems. A continuous hydrological model was used to simulate inflow of the reservoirs. Moreover, minimum, and ideal environmental flow regimes were defined based on the results of the instream flow incremental methodology (IFIM) in the reservoir operation model. IFIM is a known integrated method to assess environmental flow regime that has been applied in many previous studies (more details by Maddock, 2018). This approach was applied to assess the environmental flow of the study area in the previous study (Abdoli et.al, 2020). Results of the assessment study were applied to define minimum and ideal environmental flow regimes in this research work. The main novelty of this research work is to develop a new form of the operation model to optimize the environmental flow regime in the multireservoir systems. In fact, a framework is developed in which minimum ecological flow regime and ideal ecological flow regime could be defined as the minimum and target of the environmental flow regime in the optimization model. This approach is able to utilize outputs of the environmental flow scenarios or ecological protection scenarios in the reservoir operation optimization directly. Moreover, this research work develops a novel model to optimize environmental flow and water supply simultaneously. The main advantage of the proposed model is to consider different ecological protection levels to optimize environmental flow of the reservoirs.

The section 8.6 develops a novel optimization framework for the operation of the reservoirs in which economic benefits of irrigation supply and hydropower production is linked with the ecohdyraulic assessment of the environmental flow to minimize reservoir operation losses and ecological impacts at downstream. The main advantage of the proposed method is to minimize negotiations between farmers, reservoir managers and environmentalists in the managing large dams. The proposed method opens new windows regarding environmental sustainability in the reservoir operation. In other words, the proposed method is able to integrate benefits of the reservoir in terms of food and energy and environmental degradations at downstream. The main output of the developed optimization system is to maximize hydropower production and food production revenue by the reservoir while alleviating ecological degradations at downstream river habitats.

## ***8.1 Using wetted perimeter method for assessing environmental flow (Framework 1)***

### 8.1.1 Overview on the methodology

It might be useful to have an overview on the method. Figure 8-1-1 displays the flowchart of the proposed method that should be described. At the first step, we collected recorded historic flow and wetted perimeter in the representative reach at downstream of the river before construction of dam. It was needed to complete data for developing wetted perimeter (WP) curve. Thus, 1D hydraulic simulation was utilized to simulate wetted perimeter in different flows. Total available data was applied to develop wetted perimeter curve. In the next step, habitat loss function was generated based on the WP curve. Moreover, water demand loss function was developed as well. Then, these loss functions were applied in the structure of the reservoir operation model to optimize environmental flow. Due to using different evolutionary algorithms in the optimization process, the decision-making system was applied to select the best algorithm and finalize the environmental flow in the case study.

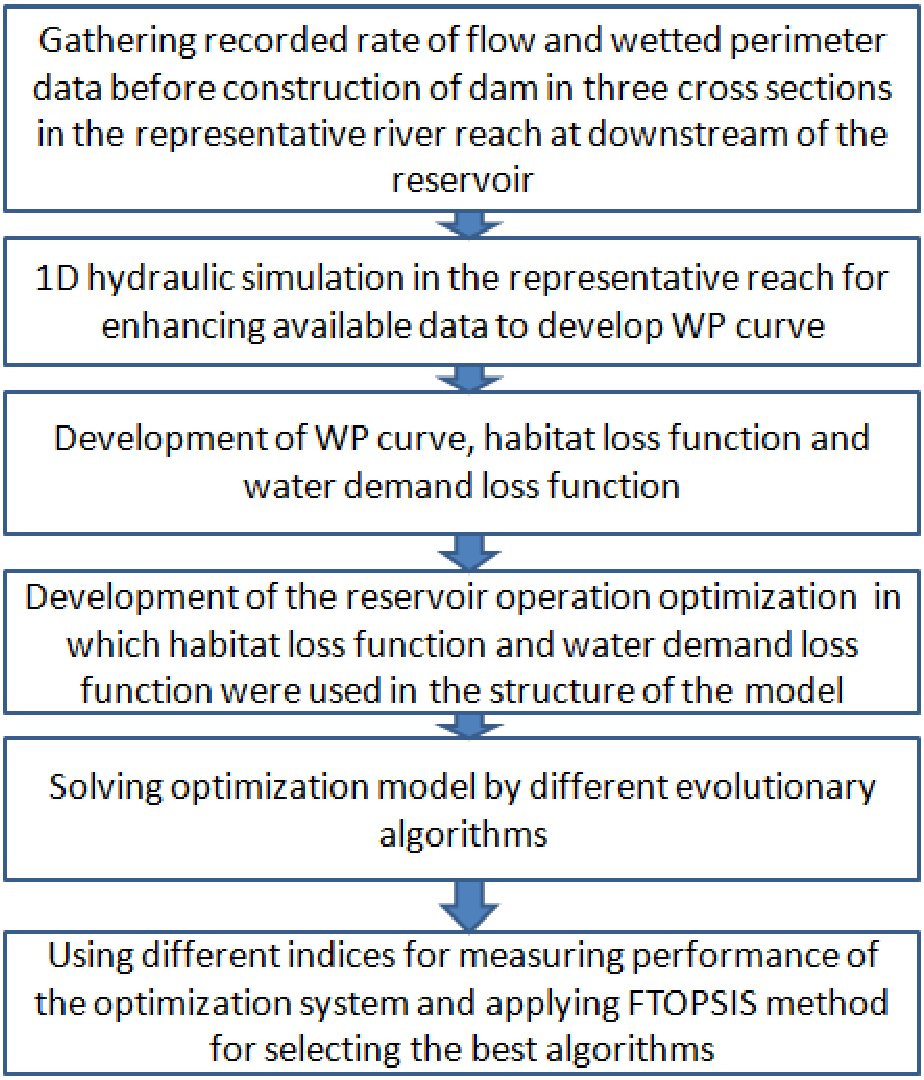



**Figure 8-1-1- Flowchart of the proposed methodology**

### 8.1.2 Study Area and problem definition

Latian Dam is one of the important constructed dams in Tehran province, Iran. This dam is responsible for supply water demand that has been constructed on the Jajrood River. This river originates from Alborz Mountains toward the salt lake with the length of 40 Km. Location of Jarood basin at the upstream of Latian dam has been displayed in Figure 8-1-2. Due to increasing population, water supply in Tehran province is a challenging issue that means optimal management of water supply is a sensitive task for regional water authority. Moreover, environmental values of the Jajrood River is not negligible. Hence, supply of environmental flow should be highlighted as well. It is required to optimize release for environment and water supply simultaneously. Hence, environmental flow assessment methods should be converted to the simulation-optimization method. WP was selected as an acceptable method to assess environmental flow due to the following considerations. First, WP is a simple and inexpensive method. It is a proper method in many cases because it is a cheap and straight-forward method to assess environmental flow. Hence, development of a simulation optimization method based on the WP method might advantageous for our case study and other similar case studies. Secondly, available instream flow at downstream of the reservoir in the current condition is very low. Hence, ecological field studies were not possible that means habitat based methods are not implementable.

It is needed to explain the effectiveness of the present method in the case study. There is no diversion project at upstream river of the dam that means sufficient flow is available at the upstream river. Before construction of dam, the fishes were able to immigrate from the downstream of the Jajrood River to the upstream for reproduction. However, construction of dam disconnected the habitats at upstream and downstream. In fact, the fishes at downstream must utilize downstream river of the dam for reproduction in the current condition. Dam considerably changed hydraulic condition of the river. Due to high water demand from the dam, no flow or very low flow is considered as the environmental flow that means the biological activities of the aquatics have been stopped in the current condition. In other words, very low depth, velocity and habitat area at downstream river of the Latian dam is drastically destructive for river ecosystem in terms of several aspects. First, depth is not sufficient for hatching. Secondly, inappropriate depth and velocity reduces food sources for the fishes. Thirdly, due to low velocity, deposition of fine particles fills voids between the gravel particles that are necessary for reproduction process of the fishes. Thus, the presented method is an effective method that is able to provide proper hydraulic and geomorphological condition at downstream river habitats and optimal reservoir operation simultaneously.

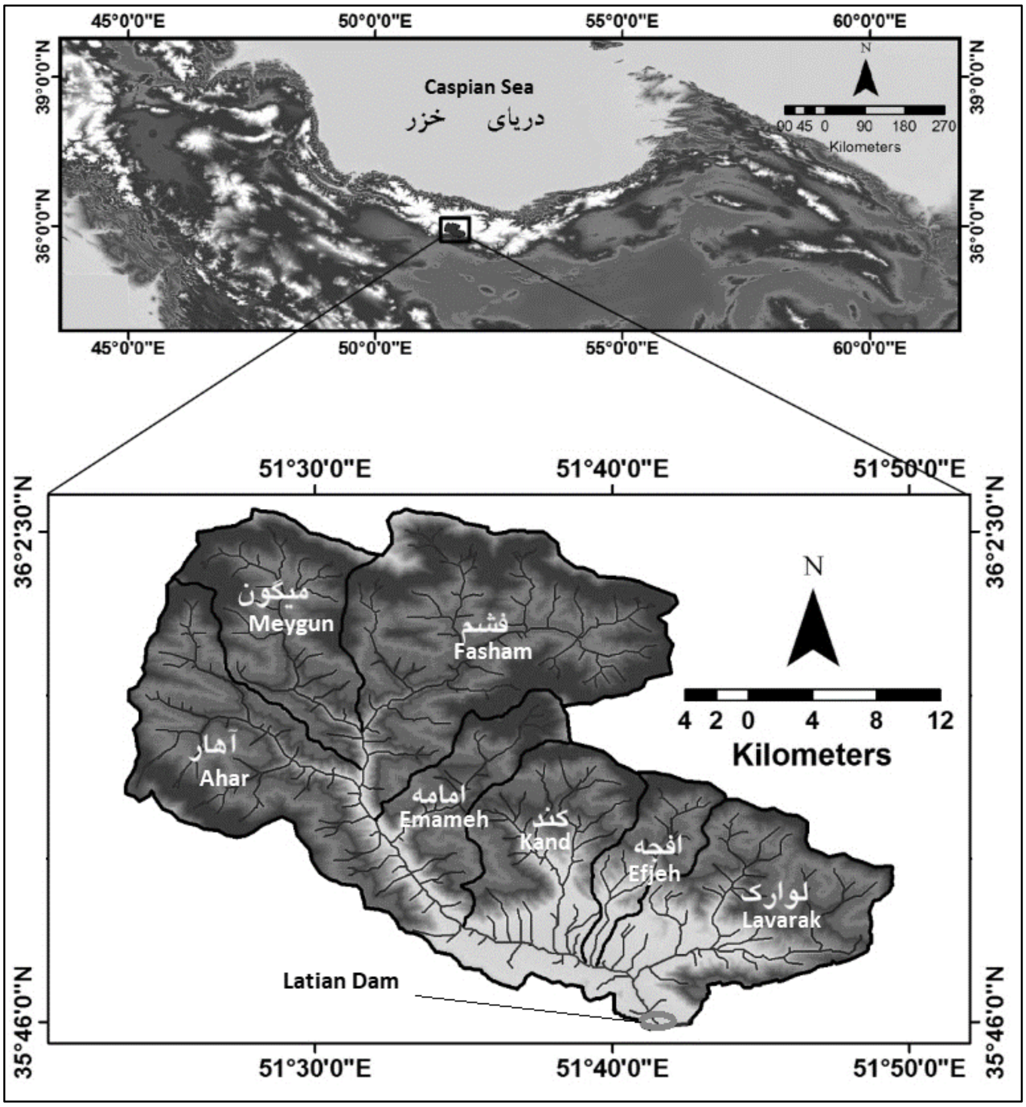



**Figure 8-1-2-Jajrood river basin map**

### 8.1.3 Wetted perimeter method

Surveyed cross sections and recorded data before construction of dam was utilized to develop 1D hydraulic model. It should be noted that results of 1D hydraulic model was used to enhance used data for developing wetted perimeter (WP) curve. In fact, three cross sections were selected in the representative reach at downstream of the reservoir with length of 5000 meters in which hydrometric stations were available to measure flow and wetted perimeter. Recorded data before the construction of dam in these points was utilized to develop WP curve. Based on surveying at downstream cross sections, their shape was relatively close to rectangular. Results of hydraulic simulation demonstrated that logarithmic relationship between wetted perimeter and discharge is the best possible relationship which corroborated proposed relationship by Gippel et.al, 1998. Equation 1 shows proposed average wetted perimeter-discharge relationship at studied downstream reach.

$$NWP = 10.4Ln(MF) + 58.9 \qquad (1)$$

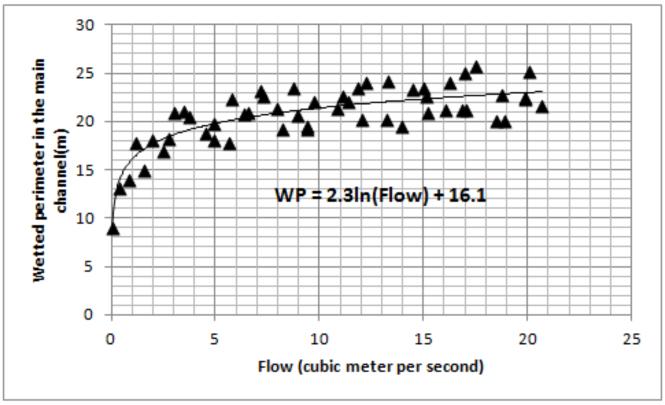
where NWP is normalized wetted perimeter(%) and MF is average monthly flow in million cubic meters. NWP considers maximum possible wetted perimeter 100% which approximately occurred in 52 mcm. In fact, WP was normalized based on the maximum wetted perimeter in the main channel. Based on the recorded data before construction of dam, it had been occurred in the 20.06 $m^3/s$. In other words, the maximum wetted perimeter in the main channel was occurred in this river flow. This value is equal to average monthly flow of 52 mcm. According to this equation, slope method and curvature method would define break point at 10.4 and 7.3 mcm respectively. These values considered as the best possible value for environmental flow requirement at downstream which would minimize habitat loss of downstream reach. Both of values have been used in optimization process and relevant analysis. It is necessary to clarify definition of the break point in the WP method. It is necessary to clarify definition of the break point in the WP method. Break point indicates required instream flow to minimize physical habitat loss in the river. In other words, basic study for developing WP method demonstrated when wetted perimeter is equal to break point; physical habitat loss is acceptable that might be considered as the optimum point in the assessment of environmental flow. The following equations indicate how break points by slope method and curvature method were computed respectively.

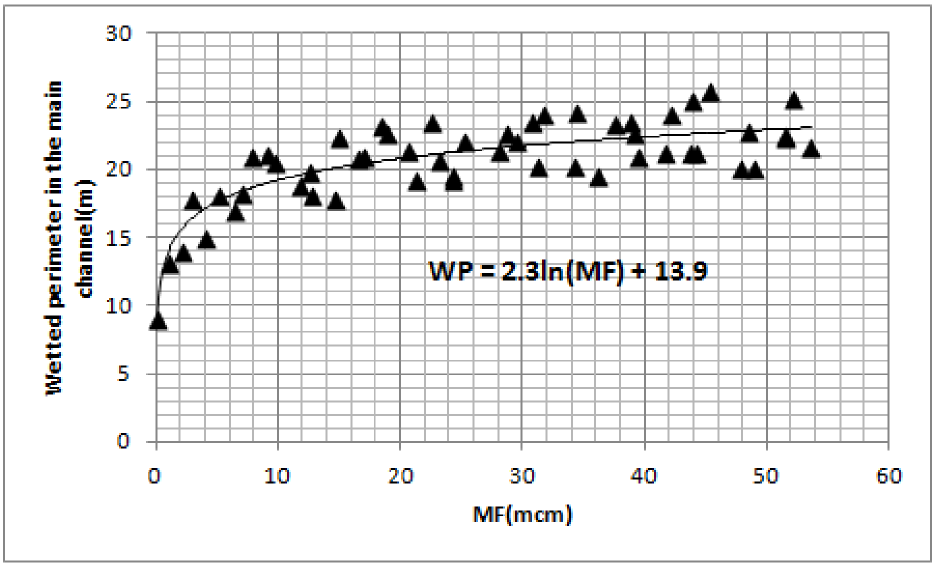
$$\frac{dP}{dQ} = \frac{10.4}{Q} = 1 \rightarrow Q = 10.4\,mcm \qquad (2)$$

$$k = \frac{\left|\frac{-10.4}{Q^2}\right|}{\left[1+(\frac{10.4}{Q})^2\right]^{1.5}} \rightarrow \frac{dk}{dQ} = 0 \rightarrow Q = 7.4\,mcm \qquad (3)$$

It is essential to explain regarding ecological evaluation of WP method. This method is a simplified method of physical habitat simulation that has been evaluated ecologically in the previous studies. In fact, it has been demonstrated that if instream flow is more than required flow equal to break point of the WP curve, suitable physical habitat is provided or physical habitat loss is acceptable that might be an optimum point in the environmental flow assessment. It might not be a perfect ecological assumption for all of the cases. However, it is a reliable assumption in the cases in which ecological field studies is not possible due to lack of instream flow for fish observations. In fact, WP method has originally been developed to assess environmental flow in cases that fish observations are not possible to apply physical habitat simulation (More details by Sedighkia et.al, 2017 and Gippel and Stewardson, 1998).

Figure 8-1-3 displays how equation 1 was developed. In the first step, relationship between daily flow and wetted perimeter was developed based on the recorded wetter perimeter in different flows before construction of the dam in the main channel of the river. Then, daily flow was converted to the monthly flow to develop proper relationship for applying in the reservoir operation optimization. Finally, WP was normalized based on the maximum wetted perimeter in the main channel of the river reported by regional water authority.




$$NWP = 10.4Ln(MF) + 58.9$$

**Figure 8-1-3- Methodology of developing normalized wetted perimeter equation**

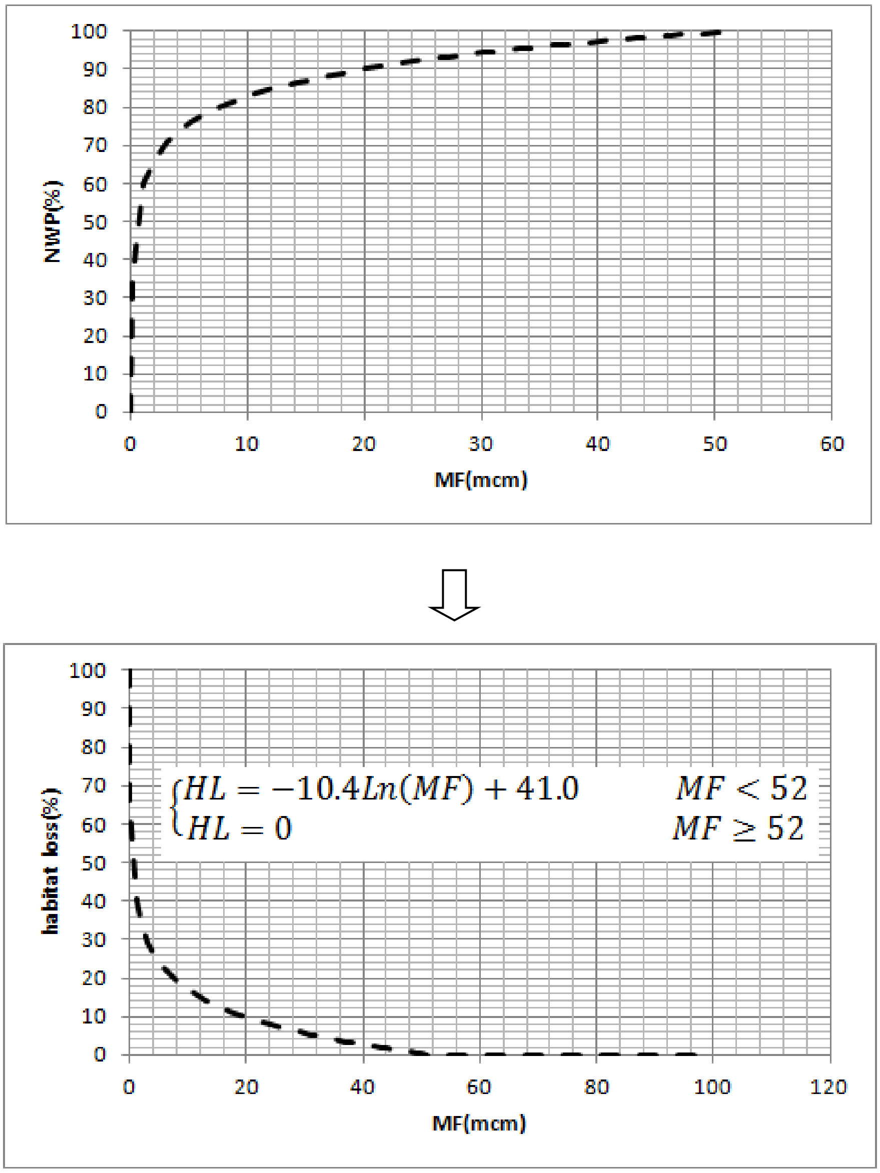



**Figure 8-1-4- Development of habitat loss function in the optimization model**

## 8.1.4 Objective function

Main component of optimization model was objective function. Hence, definition of favorite objective function was the most important step in optimization model. The main purpose of proposed methodology was to minimize conflict between water demands and environmental flow requirement by considering technical constraints. Hence defining loss function of habitats and water demand was necessary. Equation 1 considered as habitat loss function. Based on wetted perimeter method, occurring maximum possible wetted perimeter in river would provide best habitat suitability in river (Shang, 2008). However, break point was considered as minimum requirement in initial form of this method. Equation 2 displays final defined habitat loss function

$$\begin{cases} HL = -10.4Ln(MF) + 41.0 & MF < 52 \\ HL = 0 & MF \geq 52 \end{cases} \tag{2}$$

where HL is habitat loss(%). This function demonstrated that when monthly flow is more than 52 mcm habitat loss would be zero. It is required to describe how threshold of 52 mcm was selected in the habitat loss function. In fact, maximum wetted perimeter method in the main channel is equivalent with 52 mcm as the average monthly flow in the river. The main assumption of the WP method is that relationship between biomass and the flow in the main channel might be direct and linear that means 52 mcm might provide zero habitat loss. It is the highest possible flow in the main channel of the river. It seems that this threshold is robust to define habitat loss function in the main channel of the river. It should be noted that break point might provide optimal habitat loss that is acceptable to assess environmental flow based on the literature.

The next loss function which is needed would be water demand loss function. According to available demands, maximum estimated water demand predicted 30 mcm monthly. Less possible values would reduce maximum possible covered population which means increase in water demand losses. Based on stated definition on water demand, loss function of water demand has been displayed in equation 3

$$\begin{cases} DL = -3.26(MF) + 100 & MF < 30 \\ DL = 0 & MF \geq 30 \end{cases} \tag{3}$$

Objective function was defined to minimize difference between habitat loss and demand loss which is displayed in Equation 4 in which HL is habitat loss and DL is water demand loss.

$$Minimize(OF) = \sum_{t=1}^{T}(HL_t - DL_t)^2 \tag{4}$$

It is also essential to explain how the optimal value of an environmental flow is assessed in the optimization model. Equations 2 and 3 were directly utilized in the optimization model. This model tries to minimize habitat loss and water demand loss simultaneously in each time step. The best value for the environmental flow is 52 mcm that could not be supplied due to constraints in the reservoir management in terms of storage and water demand supply. However, optimal value of the environmental flow in the WP method is rate of flow in the break point in which physical habitat loss is acceptable. In this research work, physical habitat loss in the break point is 20% approximately that seems acceptable ecologically (Figure 8-1-4). It should be noted that supply of rate of flow in the break point might not be possible due to constraints in the reservoir management and importance of maximum supply of water demand. Hence, the developed optimization model is able to provide a fair balance between demand and environmental flow. In fact, optimal environmental flow proposed by the optimization model was compared with the break point as the acceptable value for environmental flow. In fact, if optimized environmental flow is able to supply break point of the WP curve in each time step, the performance of the optimization model in that time step is perfect. In other words, break point was considered as the ideal environmental flow in the measurement of the optimization system.

The optimization model is able to provide a fair balance between human's needs and aquatic needs. However, it is not able to supply needs perfectly. In fact, losses are not zero in different time steps. If inflow is high (especially in the wet seasons), it might be possible to reduce losses close to zero. However, in the average inflow or dry seasons, it is not possible to supply ideal environmental flow or total water demand. Thus, losses might not be zero in many simulated period expect wet seasons. The optimization model is able to minimize conflicts by minimizing losses for human's needs and aquatic needs.

Some points should be noted regarding the definition of the objective function. Minimizing habitat loss and water demand loss is the ideal condition that might not be possible for study areas in arid and semi-arid regions such as our case study. In fact, low inflow and lack of sufficient storage capacity might escalate conflict of interests. This new form of the objective function might balance habitat loss and water demand loss fairly. Moreover, if we consider simultaneous minimization of losses by a multiobjective model, we will need a multiobjective optimization algorithm that might not be able to provide optimal solution for defined optimization model. More details are presented in the discussion regarding advantages of the proposed optimization model. Reservoir storage in each step was calculated based on equation 5 where S is storage, I is inflow to reservoir, RF is released environmental flow, D is water demand, SP is overflow, E is evaporation and A is surface area of reservoir

$$S_{i+1} = S_t + I_t - RF_t - D_t - SP_t - \left(\frac{E_t \times A_t}{1000}\right), t = 1,2, \dots, T \qquad (5)$$

It should be noted that total of released environmental flow and over flow could define as total environmental flow to downstream reach of river. Overflow would be estimated based on maximum storage of reservoir by equation 6

$$\begin{cases} if\left(S_i + Q_{in(i)} - \left(\frac{E_i \times A_i}{1000}\right)\right) \geq S_{max} \rightarrow Q_{SP(i)} = S_i + Q_{in(i)} - \left(\frac{E_i \times A_i}{1000}\right) - S_{max} \\ if\left(S_i + Q_{in(i)} - \left(\frac{E_i \times A_i}{1000}\right)\right) < S_{max} \rightarrow Q_{SP(i)} = 0 \end{cases} \qquad (6)$$

Storage has to be between minimum and maximum limitations as the constraint of defined objective function. To convert constrained optimization problem to unconstrained one which could be solved by disparate heuristic algorithms, penalty function method was used (Yeniay, 2005). Two main penalty functions were added to main objective function which are shown in equation 7 where c1 and c2 are coefficients which have be determined based on sensitive analysis (Ehteram et.al, 2017).

$$\begin{cases} if S_i > S_{max} \rightarrow P1 = c1(\frac{S_i - S_{max}}{S_{max}})^2 \\ if S_i < S_{min} \rightarrow P2 = c2(\frac{S_i - S_{min}}{S_{min}})^2 \end{cases} \quad (7)$$

### 8.1.5 Evolutionary algorithms

Four evolutionary algorithms have been used to solve objective function. The first algorithm was a recently developed called as atom search optimization (ASO) which has not been used in reservoir operation optimization (Zhao et.al,2019). Second algorithm was gravity search algorithm (GSA) which has been developed based on gravity law (Rashedi et.al, 2009). Its ability to optimize reservoir issues have been corroborated (Bozorg-Haddad et.al, 2016). It has not however been used in optimizing environmental flow regime. Third algorihtm was teaching learning-based optimization (TLBO) which has originally been developed by Rao and Kalyankar, 2011 and it has successfully been used in operating reservoir (Kumar and Yadav, 2018). Besides, genetic algorithm (GA) was also selected due its previous broad application in optimization of water resources system in order to compare outputs. Figures 8-1-5 to 8-1-7 display flowchart of disparate used algorithms respectively.

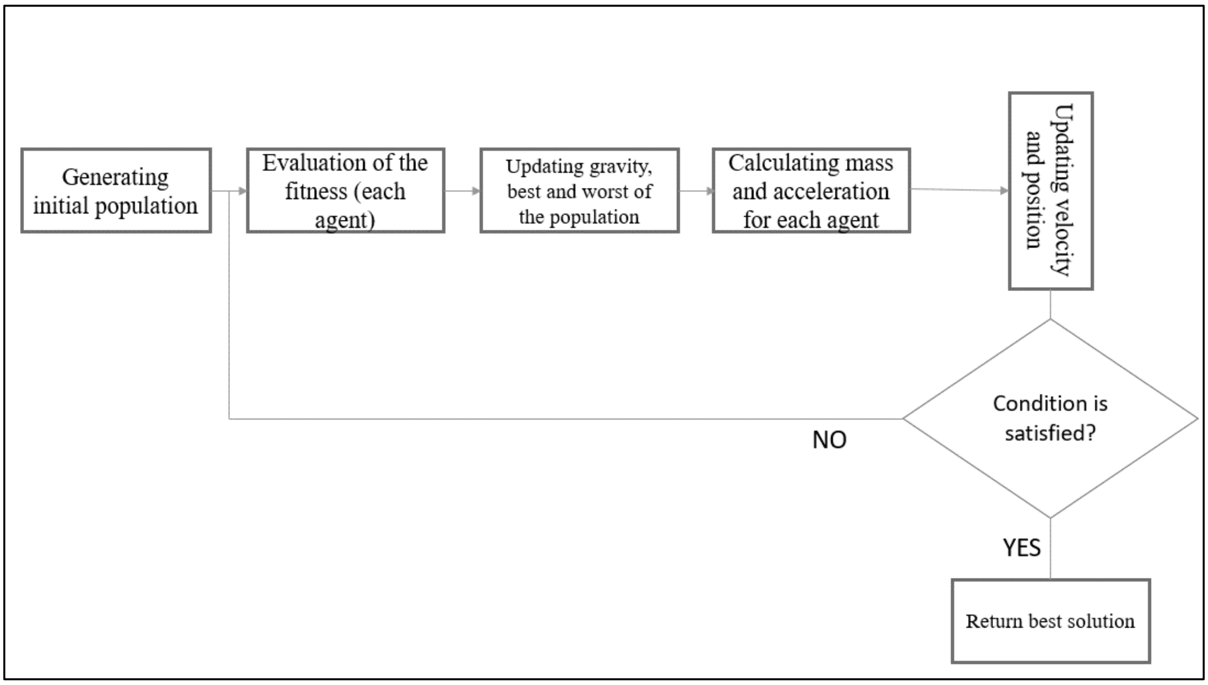



**Figure 8-1-5-Flowchart of Gravity Search Algorithm (Rashedi et.al, 2009)**

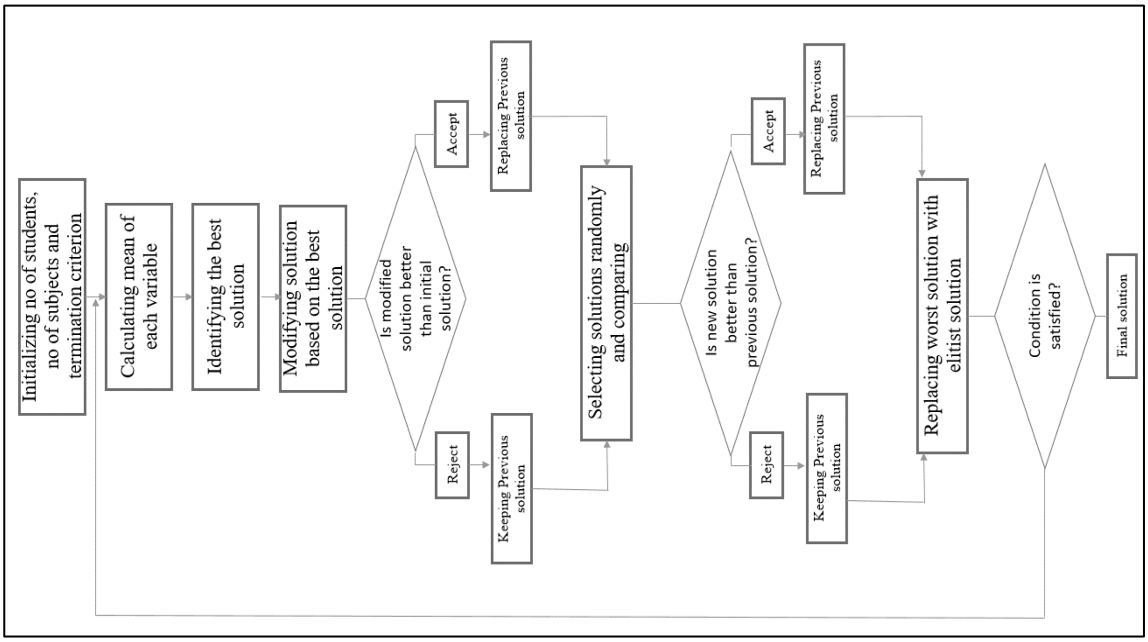



**Figure 8-1-6-Flowchart of TLBO (Rao and Kalyankar, 2011)**

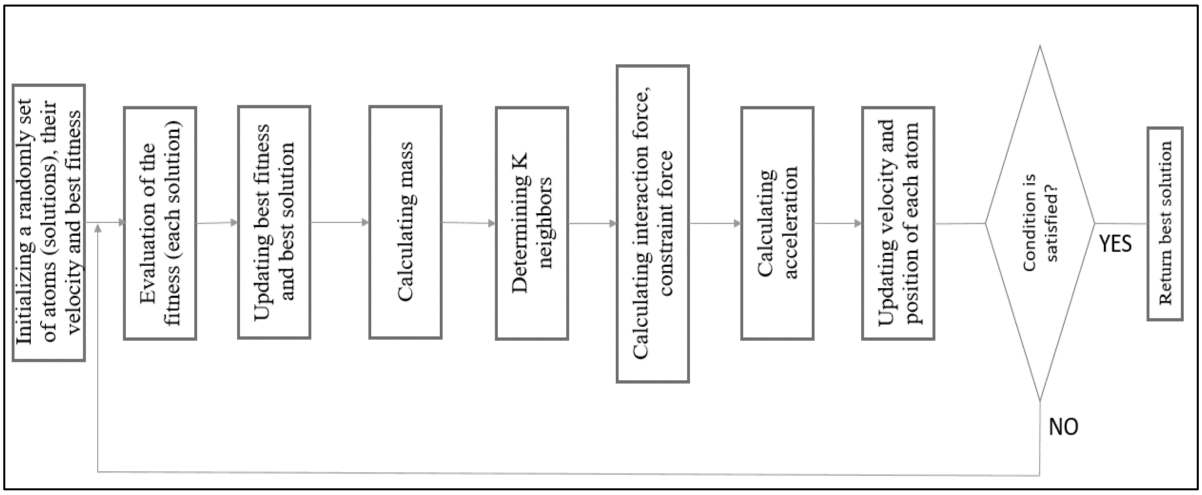



**Figure 8-1-7-Flowchart of atom search optimization (Zhao et.al,2019)**

## 8.1.6 Measurement of system performance

Some indices were selected to measure system performance of proposed optimized environmental flow regime at downstream of dam. The first index was reliability index which has originally been developed by Hashimito et.al, 1982. This index has been applied in reservoir optimization for water demand by Ehtream et.al, 2017. Equation 8 proposes designated form of this index for environmental flow regime optimization where AE is actual environmental flow and IE is ideal environmental flow by wetted perimeter method which would be evaluated based on SM and CM methods.

$$\alpha_E = \frac{\sum_{t=1}^{T} AE_t}{\sum_{t=1}^{T} IE_t} \tag{8}$$

Second index, which has been used to measure system performance is vulnerability index. It has also originally been developed and used by mentioned studies for previous index. Equation 9 proposes designated form of this index for environmental flow regime optimization

$$\gamma_E = Max_{t=1}^{T}\left(\frac{IE_t - AE_t}{IE_t}\right) \tag{9}$$

Root mean square (RMSE) is another index as system performance in this research work, which is displayed in equation 10. Another useful and applicable index to measure system performance was mean absolute error (MAE) which is displayed in equation 11(Chai and Draxler, 2014)

$$RMSE = \sqrt{\sum_{t=1}^{T} \frac{(IE_t - AE_t)^2}{T}} \tag{10}$$

$$MAE = \frac{\sum_{t=1}^{T} |IE_t - AE_t|}{T} \tag{11}$$

### 8.1.7 Decision Making System

Due to utilizing different evolutionary algorithms, one of the important purposes of this research work is to rank used methods for optimizing environmental flow regime at downstream of the reservoir which would be helpful for further studies on optimization of environmental flow regime. Fuzzy technique for order preference by similarity to ideal solution (F-TOPSIS) which has been used as applicable decision-making systems in many branches of science was selected to prioritize proposed solutions. More details are available in chapter 7.

### 8.1.8 Results and Discussion

Figure 8-1-8 displays optimal environmental flow regime by different heuristic algorithms. The performance of different algorithms in terms of environmental flow assessment is not the same. As an illustration, GA proposes a wide range of environmental flow at different months where changes between relatively close to zero to 25 mcm. TLBO however proposes 20 mcm as maximum environmental flow; meanwhile ASO provides environmental flow between 1 to 10 mcm in different months. Moreover, GSA is minimally varied in proposed environmental flow regime at downstream of dam where can be seen that the minimum value of proposed environmental flow is 4 mcm and its maximum is 7 mcm.

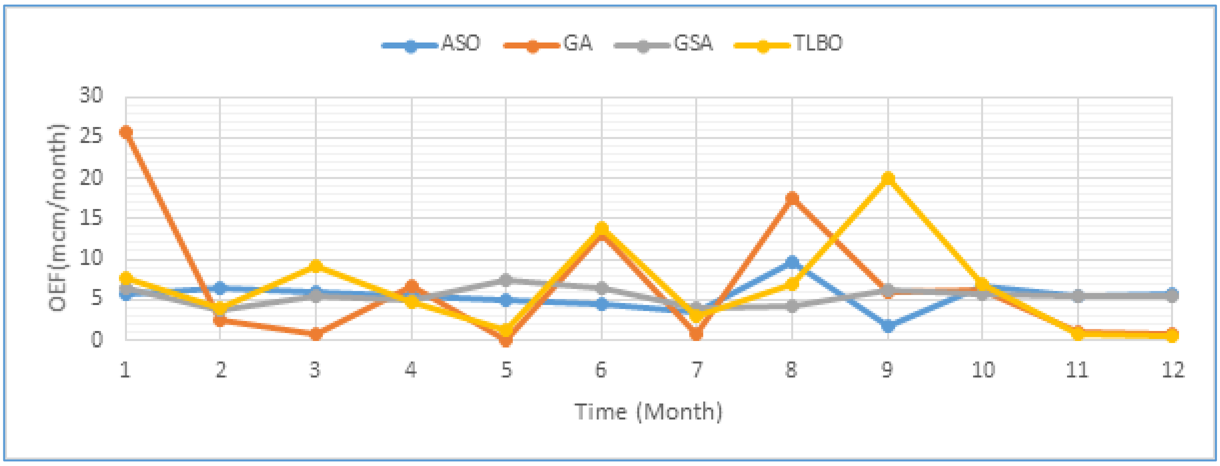



**Figure 8-1-8-Proposed environmental flow regime by different algorithms**

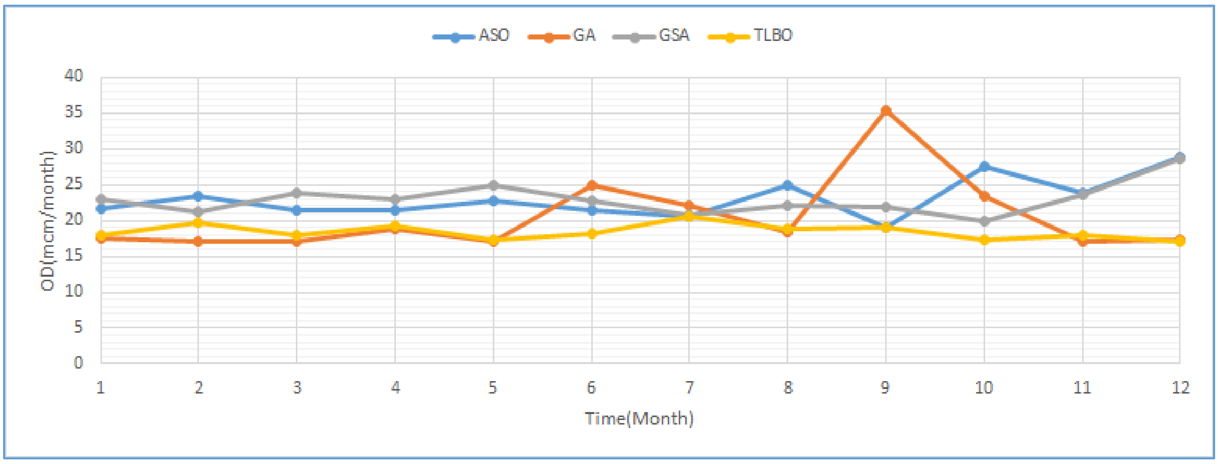



**Figure 8-1-9-proposed water supply by different algorithms**

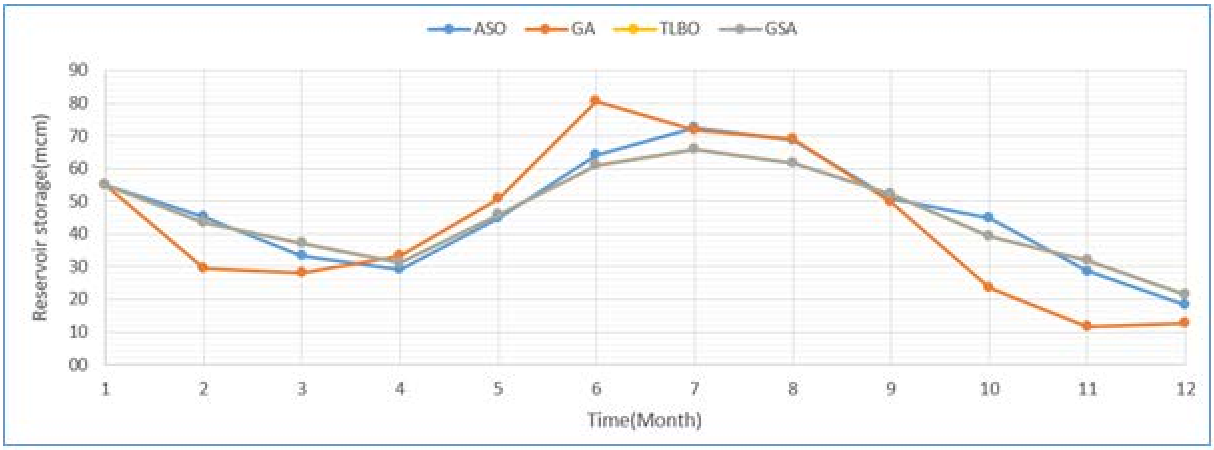



**Figure 8-1-10-Changes of reservoir volume by different algorithms**

Figure 8-1-9 presents supplied water demand regarding either GA or other non-animal inspired algorithms. Seemingly, performance of algorithms is different in supply of water demand. TLBO has the weakest performance in water demand, meanwhile either GSA or ASO is relatively similar in proposed supplied water demand. Different performance of algorithms in proposed environmental flow regime and water demand makes it necessary to measure system performance and selecting the best algorithm to optimize environmental flow regime. Figure 8-1-10 displays changes of the storage in the reservoir in the simulated period. GSA and ASO are the best methods due to less alteration of storage level in the simulated period. However, measuring the performance of the optimization system is to investigate the performance of the optimization system in terms of environmental flow supply as well. Figure 8-1-11 shows the reliability index of environmental flow supply. GA is the best method in terms of reliability of environmental flow supply. As presented, using other indices for measuring the performance of the optimization system in terms of environmental flow supply is essential. According to the Figure 8-1-12, GSA is the best method for optimization of environmental flow in terms of vulnerability index. However, the performance of GA or TLBO is weak in this regard. Figures 8-1-13 and 14 displays RMSE and MAE of environmental flow supply. The better performance of GSA in terms of MAE and RMSE is observable. It seems that the performance of GA or TLBO is not robust in terms of RMSE and MAE as well as vulnerability index.

The difference between slope method and curvature method in measurement of performance should be discussed as well. According to the results, due to higher proposed environmental flow by slope method, all of the indices considerably have weaker performance. It should be noted that SM and CM are proposed computational methods to estimate the most favorable point of environmental flow by WP method; hence, there is no ecological evidence to identify premier computational method of break point. Results demonstrate that there is a significant difference between these two methods in optimization of environmental flow especially in some indices. As an illustration, RI is considerably higher for CM in all of the used algorithms, which indicates using the SM would reduce reliability of environmental water requirement. It seems that it would be essential to investigate necessities of using slope method in assessment of environmental flow ecologically. As a general guideline of using WP method, the CM would assess ideal environmental flow lower than SM and it would be demonstrated in optimization process that CM provides more reliability in supply of environmental flow.

Vulnerability would be another story using CM and SM. There is no significant difference between two methods, which needs to be interpreted. It is required to have focus on definition of vulnerability index to discern similarities on two methods. Hashimito et.al, 1982 proposed a precise definition on vulnerability index. According to this definition, it assesses possible magnitude of failure, which means maximum difference between ideal environmental flow and defined environmental flow by optimization process. The difference between two methods in assessment of favourite or ideal environmental flow is considerable. Given that technical issues in reservoir management and high volume of water demand, vulnerability index is not however significantly different. It would be an important point in reservoir management, because it demonstrates that methods that may have overestimation on environmental flow would not be pragmatically implementable in reservoir management and lack of directorial considerations in reservoir may make results of environmental flow assessment methods useless. It would deteriorate in river basin with populated users and water scarcities due to regular droughts.

Evaluation of habitat loss and water demand loss is another important technical issue in environmental flow optimization. The purpose of developed objective function is minimization of habitat and water demand loss. In other words, best solution should be able to reduce loss of habitat and water demand, which minimally makes conflicts between water demand between community and environment. Figure 8-1-15 displays habitat loss due to applying different algorithms. According to results, GA experienced the worst performance among all of the used algorithms. Although its habitat loss is very low in some months such as January and August but its habitat loss in some month such as May is very high which means habitat may experience large losses. Some methods such as GSA and ASO experience an average habitat loss which is approximately 20% to 25%. It should be noted that TLBO has a close performance to GA in habitat loss evaluation. Changes of demand loss has been shown in Figure 8-1-16 that demonstrates that performance of GA is not at all acceptable among all of the used algorithms. It seems that TLBO has the second rank of performance, which is better considerably than GA. Unequivocally, performance of GSA and ASO is relatively similar, and it could not be judged which methods would have the best performance by observation.

Not only performance of used algorithms is quantitatively different, but it could also be observed that different indices would disparately prioritize methods. Hence, using a decision-making system of globally prioritization is indispensable. As discussed, fuzzy TOPSIS is an intellectual quantitative tool to prioritize possible alternatives for making the best decision. According to developed methodology of fuzzy TOPSIS, Figure 8-1-17 displays structure of fuzzy TOPSIS in this research work. Second row shows criteria to make decisions for prioritization. Furthermore, third row shows different possible alternatives including algorithms in optimization or environmental flow. All of the indices have been utilized to maximize accuracy of selection process.

Given that using one expert has been considered for application of fuzzy TOPSIS in this research work, hence, proposed weight for each criterion has been displayed in Table 8-1-1. As can be seen, vulnerability index has the highest weight which is very high (VH) because aquatic habitats at downstream of dam would be sensitive to short-term damages and an immediate damage in a short-term period could destroy many inhabited aquatics and cease their biological activities such as reproduction. RMSE and MAE have similar weight because their role is relatively the same in assessment of environmental flow. These indices focus on total difference between ideal environmental flow and actual environmental flow. Hence their weights have been considered as high(H). Reliability index has the lowest weight between indices. It defines ratio of total actual environmental flow and ideal environmental flow annually without considering the differences between environmental flows in each month. As a result, it would have the lowest importance among indices.

Determining rating of candidates or alternatives for each criterion is another step to implement fuzzy TOPSIS method. Kind means how increasing or decreasing criteria would affect appropriateness of each alternative. For example, based on Table 8-1-2, reliability index should be considered as benefit, because its reduction would diminish suitability of candidates. According to this definition, relatively good (RG), very good (VG) and good (G) rating mean increasing benefit for system performance. It could however be observed that other criteria are cost for the system. For example, VG rating means related candidate would have the lowest suitability pertaining to its relevant criterion. Rating values have been considered based on comparison of developed indices for each alternative.

D+ and D- as final factors to calculate close coefficient have been displayed in Table 8-1-3. In addition to close coefficient method, modified TOPSIS method (Ren et.al, 2007) has been used to prioritize algorithms. According to Table 8-1-4, which is final result of prioritization by application of fuzzy TOPSIS method, it is demonstrated that outputs of TOPSIS and M-TOPSIS are similar. GSA is the best method to optimize environmental flow regime by using WP as simulation method.

Figure 8-1-18 shows proposed optimal environmental flow regime compared by ideal environmental flow regime. To complete discussion, it is needed to review and compare results of present study by previous studies on WP method. Shon ,2008 suggested that CM method is not a good method to assess environmental flow by WP method, meanwhile Sedighkia et.al, 2017 demonstrated that SM would have unacceptable results due to natural regime of studied river and CM was more close to natural regime of river and more implementable. It seems that choosing best method to estimate break point by WP method would be dependent on natural regime of studied river. Moreover, when the goal of study is to assess environmental flow regime at downstream of large reservoirs, it is important to consider technical issues on reservoir management and water demands to finalize environmental flow regime. Optimization of environmental flow corroborated that CM is the better method to reduce conflicts between environmental requirements and water demands by stakeholders. Due to importance of the natural flow regime, Figure 8-1-19 displays monthly natural flow regime. Results corroborate that SM is not an appropriate method to assess environmental flow and it could not be supplied even in the natural flow regime without considering offstream flow.

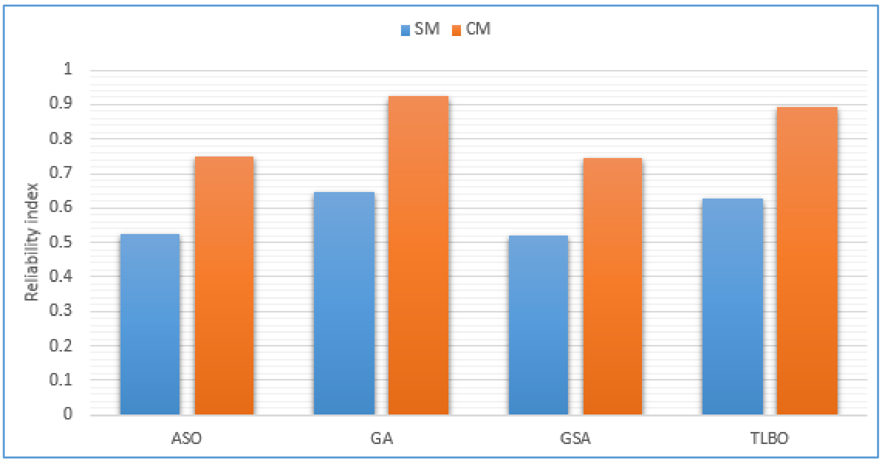



**Figure 8-1-11-Reliability index (RI) for different algorithms**

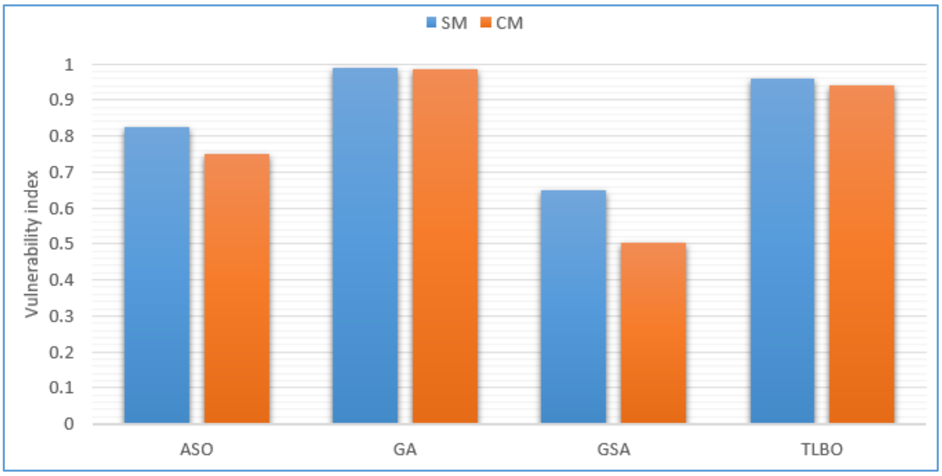



**Figure 8-1-12-Vulnerability index (VI) for different algorithms**

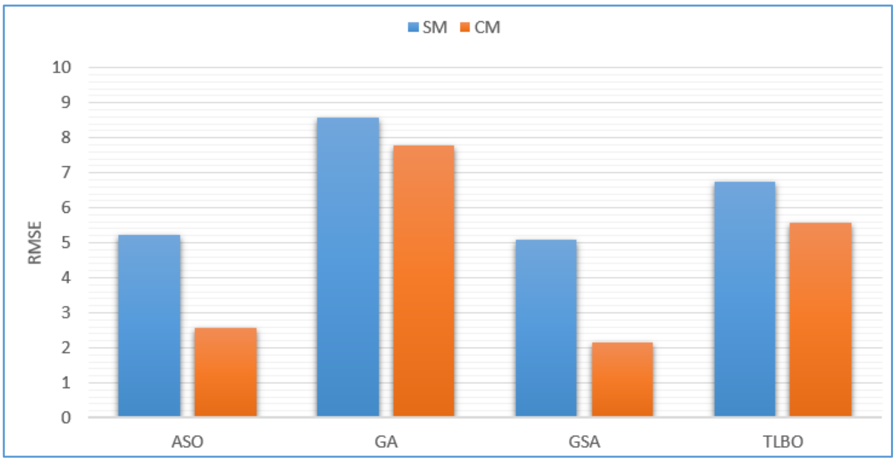



**Figure 8-1-13-RMSE index for different algorithms**

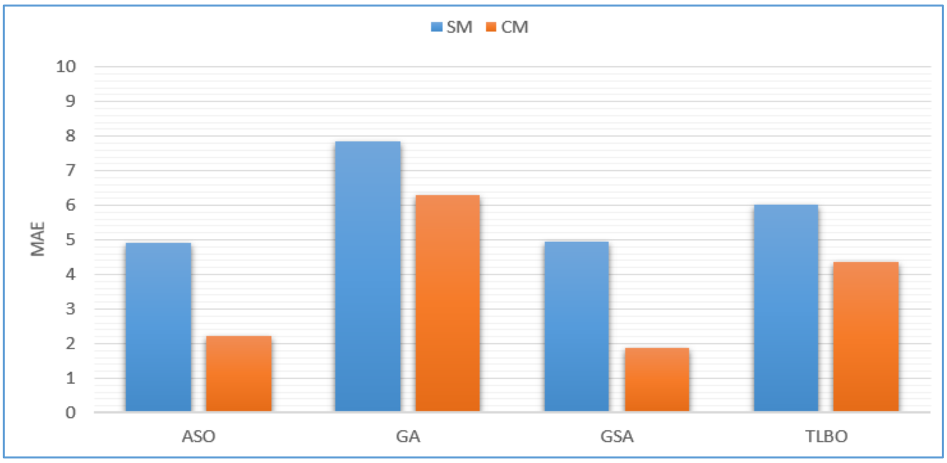



**Figure 8-1-14-MAE index for different algorithms**

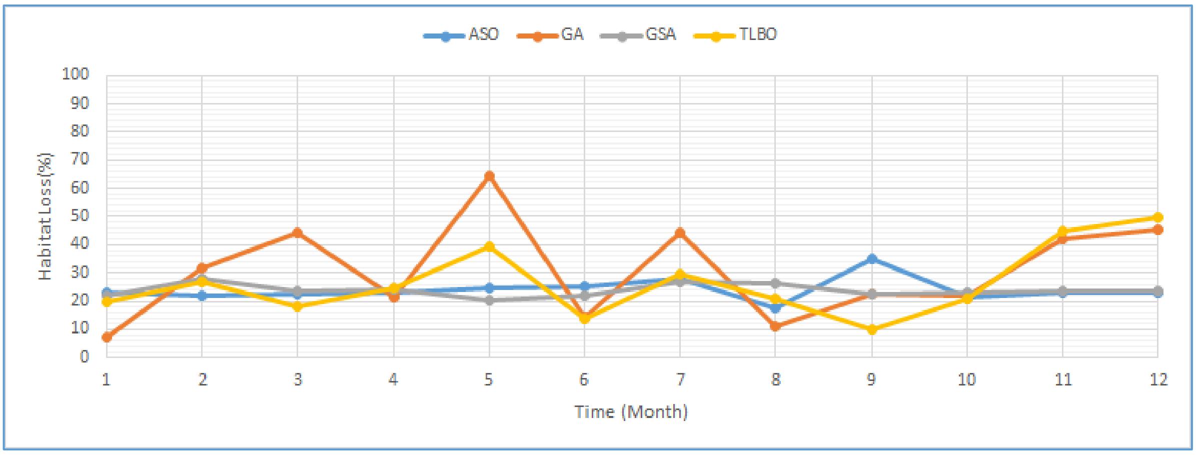



**Figure 8-1-15-Habitat loss time series for different algorithms**

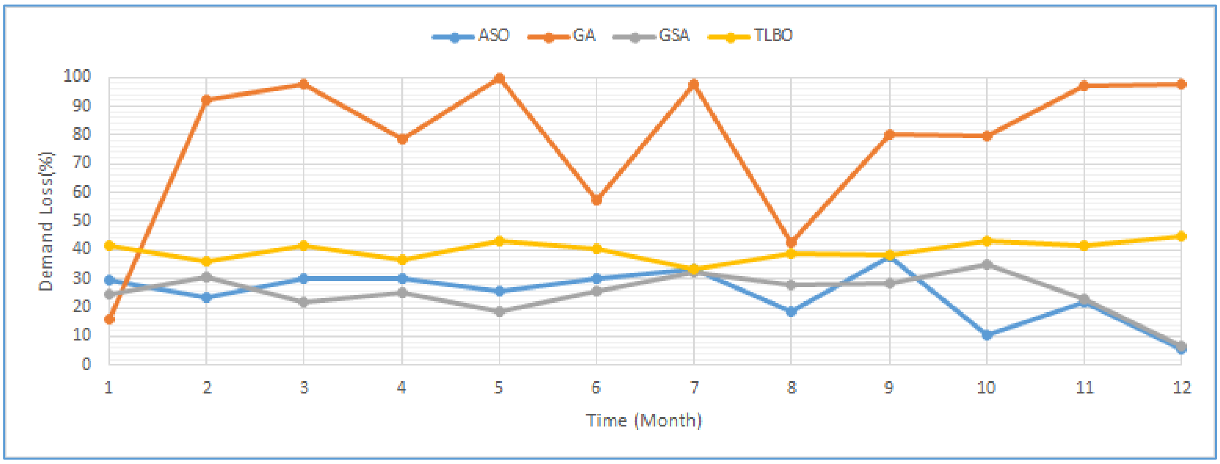



**Figure 8-1-16-Water supply loss time series of different algorithms**

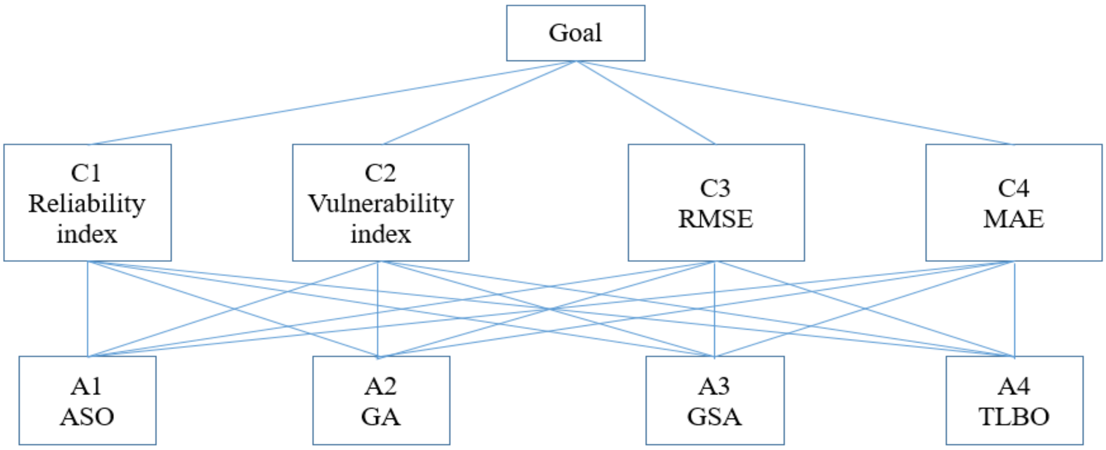



**Figure 8-1-17-Developed hierarchical structure of fuzzy TOPSIS method**

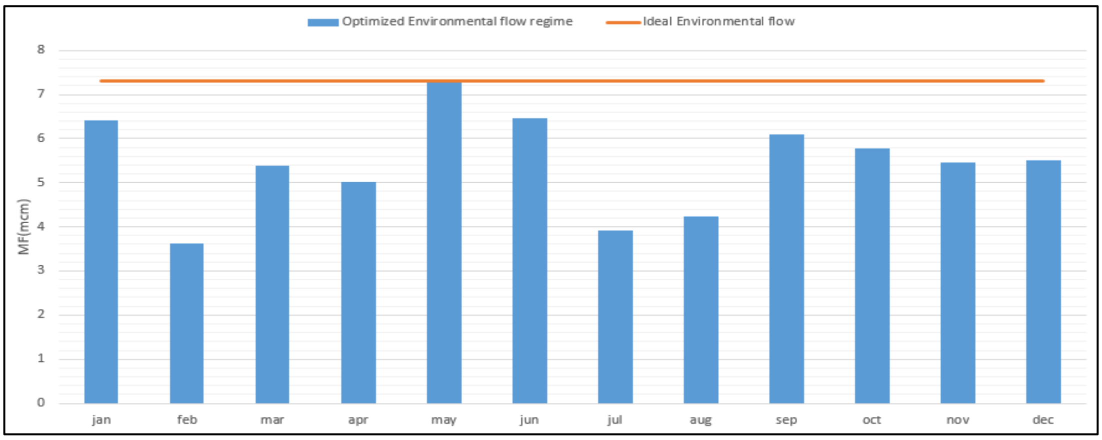



**Figure 8-1-18-Finalized optimal environmental flow regime**

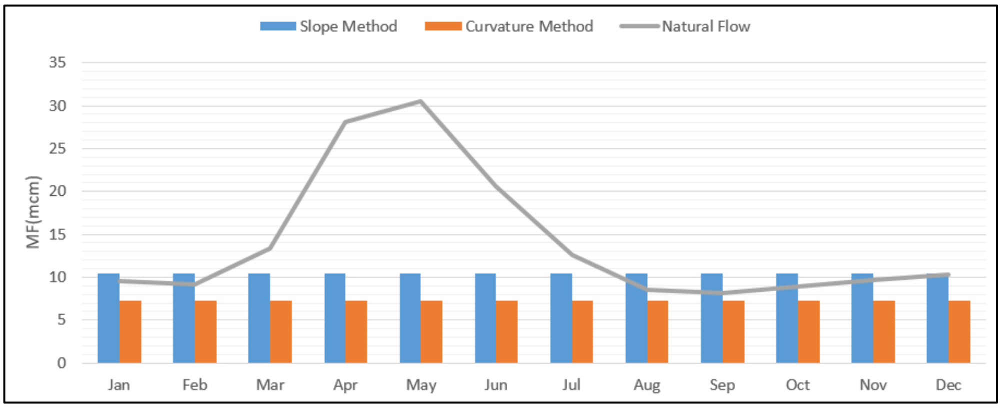



**Figure 8-1-19-Natural flow regime at downstream of studied dam**

Some points should be discussed regarding the proposed optimization framework. According to the results, wave-like fluctuations occur in the calculated environmental flow regime by some algorithms such as GA and TLBO. It should be noted that the main problem for using evolutionary algorithms in the optimization process for complex objective function such as defined function in this research work is lack of ability to guarantee the global optimization. Hence, some algorithms might provide unnatural responses for the complex optimization problems such as TLBO and GA in this research work. Interestingly, weaknesses of GA and TLBO are reflected in the RMSE and MAE. In fact, high RMSE for these algorithms demonstrates that they are not appropriate for the optimization process in this research work. Moreover, decision-making system indicates that these two algorithms are not appropriate for optimizing environmental flow in the proposed method.

Another solution for defined optimization problem is to apply a multiobjective optimization algorithm. In fact, minimization of habitat loss and water demand loss could be considered as two objective function in the system. At the first glance, it seems logical to utilize this type of the optimization. However, some points might weaken the applicability of the multiobjective model for the case study. From the technical view, simultaneous minimization of losses in the case study is not possible due to lack of stream flow and storage capacity in the reservoir. In other words, multiobjective model might not be able to balance losses fairly. From the computational view, some drawbacks should be noted regarding the multiobjective model. First, evolutionary algorithms are not able to guarantee the global optimization that means using different algorithms is necessary in the optimization process. Unfortunately, limited number of multiobjective optimization algorithms have been developed that decreases efficiency of these algorithms. Higher computational complexities is another problem of the multiobjective models. It should be noted that low computational complexities are one of the main requirements for utilizing the optimization models in practical projects. Numerous simulations and covering long-term periods are the main requirements in projects that increase computational complexities. In contrast, many single objective optimization algorithms have been developed in the literature. Hence, the developed single objective optimization model is advantageous in terms of technical and computational considerations.

Two important issues should be discussed as well. First, how four algorithms are different in terms of environmental flow or ecological impact at downstream of the reservoir. Utilized measurement indices are useful to discuss on this question. RMSE and MAE indicate how optimization algorithm might mitigate ecological impacts averagely. In fact, high RMSE or MAE demonstrates that optimal environmental flow is considerably different from the ideal environmental flow. Hence, two algorithms including GA and TLBO are not reliable because they are not able to provide a sustainable ecological status in the case study. In fact, ideal environmental flow might guarantee the sustainable ecological status in the river. Hence, high RMSE and MAE corroborate inability of the optimization method for providing sustainable ecological status in the river.

Another question is whether GSA as the best method could be considered as the best method for other case studies or addressing other methods of the environmental flow assessment. It should be noted that GSA was selected based on the defined criteria in the case study in the decision-making system. We determined weights of importance based on technical considerations in the case study. However, other cases might have other priorities in the management of the environmental flow. Thus, we do not claim that GSA is the best method for all the case studies or other methods of the environmental flow assessment. We tried to consider criteria and weight of importance perfectly in the case study that might appropriate for many cases. However, we recommend using the proposed method of optimization and decision-making system in each case study to select the best algorithm and finalizing the environmental flow regime.

As a summary on this section, we proposed a novel method to optimize environmental flow regime at downstream of large dams with focus on wetted perimeter (WP) as one of the principal methods to assess environmental flow. In other words, proposed method converts WP as inflexible method to assess environmental flow to a flexible method to optimize environmental flow regime with technical consideration in reservoir management with focus on minimization of difference between habitat loss and water demand loss. According to results, CM is a suitable method to assess ideal environmental flow at downstream of river. Although this could not provide sufficient water demand and technical limitations in reservoir management. Optimization method by utilizing different non-animal evolutionary algorithms could propose optimized environmental flow regime. Used algorithms were included genetic algorithm (GA), gravity search algorithm (GSA), atom search algorithm (ASO), and teaching-learning based optimization. What is more, a decision-making system based on fuzzy TOPSIS method has been used to select the best algorithm for optimizing environmental flow. As a result, gravity search algorithm (GSA) was selected as the best algorithm to optimize environmental flow regime by considering different criteria include reliability index, vulnerability index, root means square error and mean absolute error. Main innovation of present study is to present a coupled simulation-optimization method to optimize environmental flow regime at downstream of large dams which reduces controversial negotiations between environmental managers and stakeholders. Proposed regime could be a basic accurate estimation for further negotiations and finalizing environmental flow regime.

**Table 8-1-1- Defined weights for different criteria**

| Criterion | Reliability index | Vulnerability index | RMSE | MAE |
|---|---|---|---|---|
| **Weight** | M | VH | H | H |

**Table 8-1-2- Rating values for alternatives in disparate criteria (VG, RG, G, F and RP mean very good, relatively good, good, fair and relatively poor respectively)**

| Criteria | Kind | Candidates | Rating |
|---|---|---|---|
| Reliability index | Benefit | ASO | RG |
| | | GA | VG |
| | | GSA | RG |
| | | TLBO | G |
| Vulnerability index | Cost | ASO | RG |
| | | GA | VG |
| | | GSA | F |
| | | TLBO | VG |
| RSME | Cost | ASO | RP |
| | | GA | G |
| | | GSA | RP |
| | | TLBO | RG |
| MAE | Cost | ASO | RP |
| | | GA | G |
| | | GSA | RP |
| | | TLBO | RG |

**Table 8-1- 3- D+ and D- of candidates (D+ and D- mean distance of alternative from fuzzy positive ideal solution and distance of alternative from fuzzy negative ideal solution respectively)**

| Alternatives | D+ | D- |
|---|---|---|
| ASO | 2.50 | 2.10 |
| GA | 3.03 | 1.04 |
| GSA | 2.36 | 2.35 |
| TLBO | 3.01 | 1.09 |

**Table 8-1-4- Finalized prioritization by fuzzy TOPSIS method**

| Alternatives | CC/R | | Ranking | |
|---|---|---|---|---|
| | TOPSIS | M-TOPSIS | TOPSIS | M-TOPSIS |
| ASO | 0.456 | 2.517 | 2 | 2 |
| GA | 0.255 | 3.302 | 4 | 4 |
| GSA | 0.499 | 2.357 | 1 | 1 |
| TLBO | 0.265 | 3.268 | 3 | 3 |

## *8.2 Using physical habitat simulation for assessing environmental flows (Framework 2)*

Our methodology contains three main parts including development of the physical habitat model, development of the objective function in the optimization model and description of the evolutionary algorithms to optimize reservoir operation. We utilized the proposed framework in a case study to demonstrate its applicability to optimize reservoir operation in terms of minimizing downstream environmental impacts. This section includes the full description on the methodology, the case study and results and discussion.

### 8.2.1 ANFIS based physical habitat model

We considered two main effective physical factors consisting of depth and velocity as the inputs of the physical habitat model. Adding substrate might be essential to the model in some cases. However, the initial ecological assessment in our case study demonstrated that bed particle size is almost same in all cross sections of the representative river reach. Hence, we excluded it to develop physical habitat model.

Figure 8-2-1 displays architecture of the developed physical habitat model. We used five traingular membership functions for depth and velocity including low, medium, high and very high . We applied the Nash–Sutcliffe model efficiency coefficient (NSE) to compare outputs of the developed model with the recorded data in the testing process of the data driven model. More details regarding NSE have been addressed in the literature (McCuen et.al, 2006). We used 80% of recorded microhabitats to train the habitat model. Thus, the rest of the observed data was utilized to test performance of the model. Equation 1 displays mathematical definition of NSE in this research work.

$$NSE = 1 - \frac{\sum_{t=1}^{T} |MHS_t - OHS_t|}{\sum_{t=1}^{T} |OHS_t - OHS_m|} \tag{1}$$

where $MHS_t$ is the simulated habitat sutaility in each microhabitat, $OHS_t$ is the observed habitat suitability in each microhabitat and $OHS_m$ is the average of observed habitat suitability .

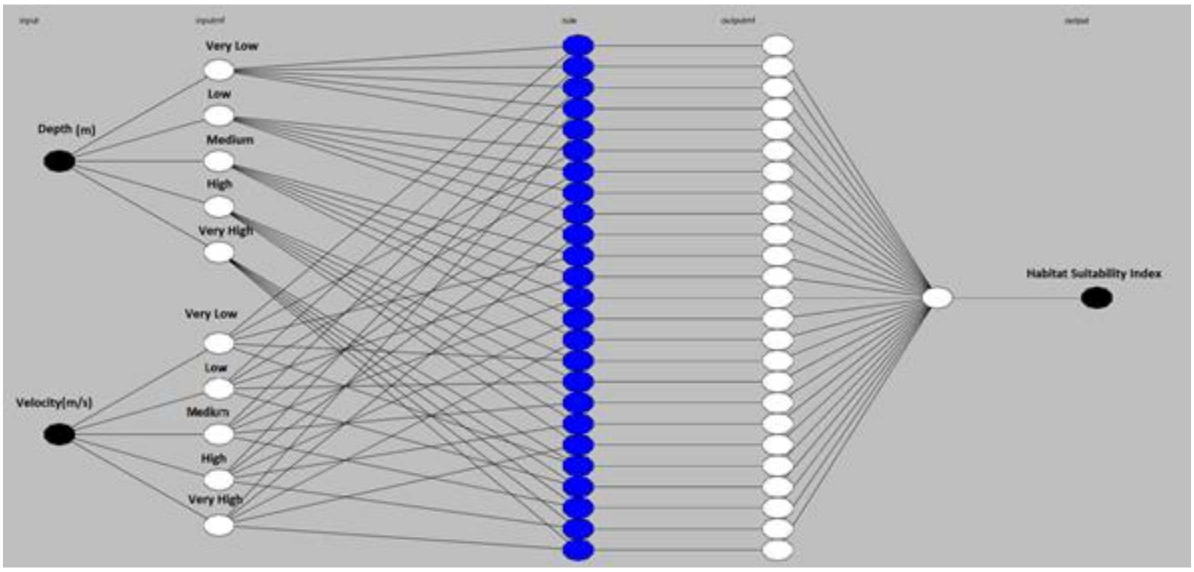



**Figure 8-2-1- Arcitecture of physical habitat model**

### 8.2.2 Objective function

The objective function is the most important component of each optimization model. In this research work, we defined objective function as displayed in the equation 2

$$\text{minimize}(OF) = \sum_{t=1}^{T} \left(\frac{NPH_t - APH_t}{NPH_t}\right)^2 + P1 + P2 \tag{2}$$

where $NPH_t$ is the natural physical habitat suitability in each time step (monthly) and $APH_t$ is the actual physical habitat suitability that would be expected by release in each time step. The penalty function is one of the solutions to solve reservoir optimization problem that is able to consider storage constraints.

In other words, this method is applicable for considering the storage constraints in the structure of the objective function. Hence, two penalty functions have been added as follows.

$$\begin{cases} if S_i > S_{max} \rightarrow P1 = c1(\frac{S_t - S_{max}}{S_{max}})^2 \\ if S_i < S_{min} \rightarrow P2 = c2(\frac{S_t - S_{min}}{S_{min}})^2 \end{cases} \quad (3)$$

where $S_t$ is storage in each time step and $S_{min}$ and $S_{max}$ are maximum storage and minimum operational storage for the best reservoir operation practice. C1 and C2 are constant coefficients that might be assessed and determined by the initial sensitivity analysis. The storage level in the reservoir would be changed in each time step of the simulation. Hence, equation 4 is applied to update storage in each time step.

$$S_{t+1} = S_t + I_t - R_t - D_t - F_t - \left(\frac{E_t \times A_t}{1000}\right), t = 1,2, \ldots, T \quad (4)$$

where S is storage, I is inflow of the reservoir, E is evaporation from the surface, A is area of the reservoir surface, R is release, D is demand and F is overflow that would be defined by the equation 5.

$$\begin{cases} if \left(S_t + I_t - \left(\frac{E_t \times A_t}{1000}\right)\right) \geq S_{max} \rightarrow F_t = S_t + I_t - \left(\frac{E_t \times A_t}{1000}\right) - S_{max} \\ if \left(S_t + I_t - \left(\frac{E_t \times A_t}{1000}\right)\right) < S_{max} \rightarrow F_t = 0 \end{cases} \quad (5)$$

It is required to describe the workflow of the simulation-optimization model. The time step in the optimization process is monthly. Management of the environmental flow is usually in the monthly scale. The main variable of the optimization model is the release from the reservoir. In fact, release from the reservoir is release for the environment or environmental flow. First, the simulation-optimization system simulates physical habitat suitability in the natural flow in each month. Then, it assumes the environmental flow in each month to simulate actual physical habitat suitability. In the next step, optimization algorithm finds the best solution (the best environmental flow regime) to minimize the objective function. Another variable is storage in the model that would be updated in each time step.

### 8.2.3 Evolutionary algorithms

Evolutionary algorithms are methods that explore random points of the solution space and then compare them to each other. The best evaluated point is given as the solution of the optimization problem. As reviewed at introduction, these algorithms are recognized as applicable and efficient methods for optimization problems. We used several algorithms for the reservoir operation optimization to compare and analyze the performance of different evolutionary algorithms. Generally, these algorithms are classified in two groups including animal and non-animal inspired algorithms (Jahandideh-Tehrani et.al, 2019). The animal inspired algorithms usually imitate the social behavior of the animals such as the movement of organisms in a bird flock or fish school. Moreover, non-animal inspired algorithms have been motivated by other phenomena such as the gravity law. Due to different origins of the evolutionary algorithms, their response might be different for an optimization problem. Furthermore, evolutionary algorithms are classified as the classic and new generation algorithms (Dokeroglu et.al, 2019). Thus, using a wide range of the algorithms is helpful to compare the robustness of the algorithms to optimize environmental flow.

We applied different algorithms including particle swarm optimization (PSO), genetic algorithm (GA), differential evolution (DE), shuffled frog leaping algorithm (SFLA), invasive weed optimization (IWO), gravity search algorithm (GSA), atom search algorithm (ASO) and bat algorithm (BA). Some algorithms such as PSO and GA are known evolutionary algorithms that might be considered as the classic algorithms. In contrast, some algorithms such as ASO have recently been developed that means they have rarely been applied in the optimization problems. General framework of these algorithms is similar. (However, they utilize different strategies to search the solution space. Table 8-2-1 shows more details regarding each algorithm. Full description is available in the cited references in the table 8-2-1.

**Table 8-2-1- More details on the used algorithms**

| Name of algorithm | Short description | Reference |
|---|---|---|
| **PSO** | stylized representation of the movement of organisms in a bird flock or fish school | (Kennedy and Eberhart, 1995) |
| **GA** | inspired by the process of natural selection by relying on biologically inspired operators such as mutation, crossover and selection | (Whitley, 1994) |
| **DE** | A known non-animal inspired algorithm that uses for multidimensional real-valued functions | (Qin et.al, 2008) |
| **SFLA** | An animal inspired algorithm based on observing, imitating, and modelling the behaviour of a group | (Amiri, et.al, 2009) |
| **IWO** | This algorithm mimics natural behaviour of weeds in | (Mehrabian and Lucas, 2006) |

| | | |
|---|---|---|
| | colonizing and finding suitable place for growth and reproduction | |
| **GSA** | A non-animal algorithm inspired by the gravity law | (Rashedi et.al, 2009) |
| **ASO** | A non-animal algorithm inspired by basic molecular dynamics | (Zhao et.al,2019) |
| **BA** | An animal inspired algorithm based on the social behaviour of the bats | (Yang and Gandomi, 2012) |

### 8.2.4 System performance measurement and decision making system

Each optimization system must be measured to analyse its performance. Given the optimization of environmental flow and storage in this research work, performance indices must be defined for release and storage separately. Two basic system performance indices including reliability and vulnerability indices (RI and VI) were applied in the measurement of the optimization system (Originally developed by Hashimito et.al, 1982). These indices have been improved in the recent studies (Ehteram et.al, 2018). We used customized form of these indices to measure system performance in this research work. Equation 1 and 2 display RI and VI respectively. Moreover, we utilized absolute error (MAE) (Chai and Draxler, 2014). Equation 3 shows how mathematical form of this index has been defined in this research work.

$$\alpha_E = \frac{\sum_{t=1}^{T} APH_t}{\sum_{t=1}^{T} NPH_t} \tag{1}$$

$$\gamma_E = Max_{t=1}^{T}\left(\frac{NPH_t - APH_t}{NPH_t}\right) \tag{2}$$

$$\mathrm{MAE}_E = \frac{\sum_{\mathrm{I}=1}^{\mathrm{T}} \mathrm{ABS}(\mathrm{NPH_t} - \mathrm{APH_t})}{\mathrm{T}} \tag{3}$$

Moreover, it is essential to define system performance indices for storage including MAE and VI. Equation 4 and 5 display storage system performance indices where $RS_t$ is required optimal storage and $OS_t$ is optimal storage by optimization model.

$$\gamma_S = Max_{t=1}^{T}\left(\frac{RS_t - OS_t}{RS_t}\right) \quad (4)$$

$$\mathrm{MAE}_S = \frac{\sum_{I=1}^{T} \mathrm{ABS}(\mathrm{OS_t} - \mathrm{RS_t})}{\mathrm{T}} \quad (5)$$

Due to using different solutions for optimization problem, it is essential to utilize a decision-making system that is able to select the best solution among the used evolutionary algorithms. Different decision making systems might be useable in this regard. We applied Fuzzy Technique of Order Preference Similarity to the Ideal Solution (FTOPSIS) as one of the efficient methods to select the most robust evolutionary algorithm. The hierarchical structure of the FTOPSIS in this research work is displayed in the figure 8-2-2.

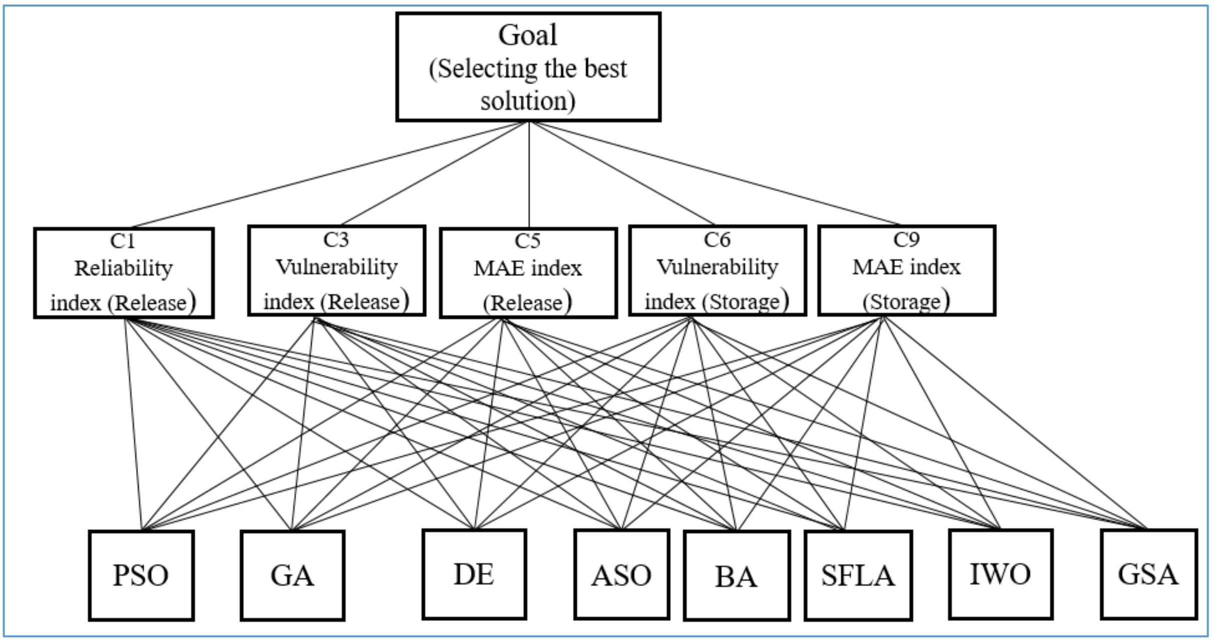



**Figure 8-2-2- Hierarchical structure of developed FTOPSIS decision-making system**

### 8.2.5 Case study

The Proposed framework has been implemented in the Latian dam as one of the largest dams in the southern Caspian Sea basin in Iran. This dam has been constructed on the Jajrood River where is mainly responsible for supply part of drinking water demand of Tehran province. Figure 8-2-3 displays location of dam and upstream river basin. It should be noted that maximum, minimum and optimal storage of dam are 95, 10 and 55 Mcm.

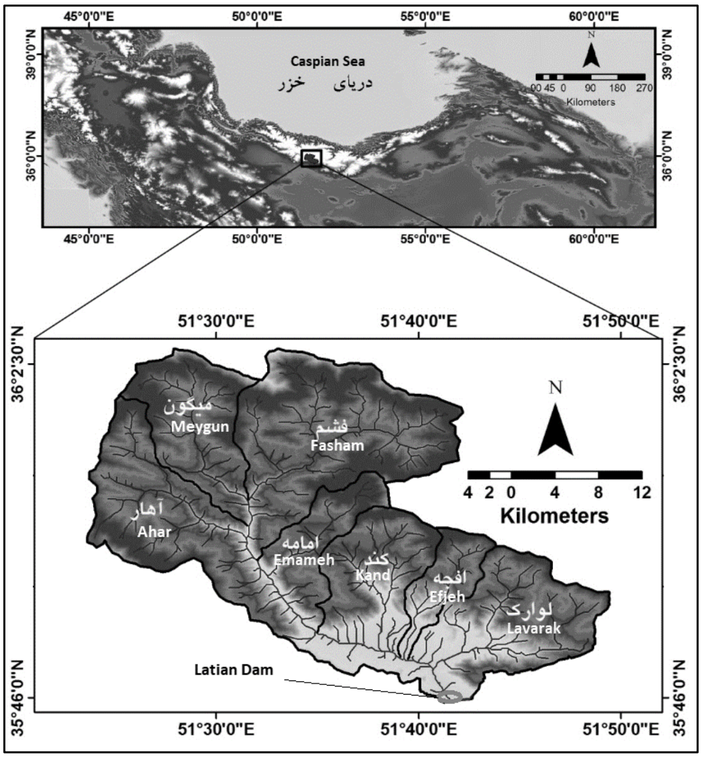



**Figure 8-2-3-Location of Latian dam and upstream river basin**

Due to sensitivity of drinking water supply in the study area, it must not be violated in the optimization system based on the recommendations by the regional water authority. Hence, water demand has been defined as a fixed time series. According to the guidelines of the regional water authority, monthly water demand is constantly $3m^3/s$. Water supply is being carried out by direct pumping from the reservoir to the pipe network. There is a serious concern regarding storage in the reservoir. On the one hand, department of environment (DOE) requests to release maximum possible flow to the downstream for protecting river habitats. On the other hand, water authority is worried about protecting optimal storage in the reservoir for other beneficial aspects of the dam such as upstream hydropower plant and strategic storage in the reservoir. Thus, utilizing an optimization system for downstream environmental flow is necessary. Figure 8-2-4 displays monthly average inflow of the reservoir from upstream tributaries that is the natural flow of the Jajrood river. Moreover, Figure 8-2-5 shows evaporation from the surface of the reservoir that is applied in the reservoir operation optimization.

Downstream River was divided to three reaches including upstream, mid and downstream reaches. According to field studies and surveying cross sections, six relationship were developed to assess mean depth and velocity at each river reach as displayed in the following equations where D is depth (meters), V is velocity (m/s) and Q is flow ($m^3/s$)

$$Upstream\ reach \begin{cases} V = -0.0026(Q^2) + (0.0927Q) + 0.0702 \\ D = -0.0013(Q^2) + (0.0791Q) + 0.0276 \end{cases} \tag{6}$$

$$Mid\ reach \begin{cases} V = -0.0033(Q^2) + (0.1062Q) + 0.0694 \\ D = -0.0007(Q^2) + (0.0715Q) + 0.0453 \end{cases} \quad (7)$$

$$Downstream\ reach \begin{cases} V = -0.0036(Q^2) + (0.1098Q) + 0.0364 \\ D = -0.0011(Q^2) + (0.0831Q) + 0.0361 \end{cases} \quad (8)$$

In fact, we utilized an average relationship for assessing depth and velocity in the representative reaches. Moreover, fish observations were required to develop physical habitat model. Purpose of the fish observations was to assess how depth and velocity would affect number of adult fish in each microhabitat. We sampled different habitats throughout the Jajrood River and tributaries to increase the accuracy of the field studies. Based on the previous ecological studies in the Jajrood river basin, Capoeta capoeta as a known fish species was selected as the target species for physical habitat simulations. Different methods have been developed to observe the fishes in the microhabitats that have been discussed in the literature (Harby et.al, 2004). Due to the advantages of electrofishing, we used this method to observe fish in the river habitats. Velocity and depth were observed and measured by propeller and metal ruler in each observed microhabitat as well as the number of the target species. More detail on the sampling methods is available in the literature (Harby et.al, 2004).

### 8.2.6 Results and Discussion

Figure 8-2-6 displays depth and velocity in each microhabitat for the testing process of the developed ANFIS based model. Based on the result, Figure 8-2-7 displays observed and simulated physical habitat suitability that was used to measure robustness of the habitat model. NSE was computed to analyse performance of the habitat model that is 0.93. When NSE is more than 0.5, predictive skills of the model is robust. In other words, the developed habitat model is reliable for further applications. We had a wide range of observed microhabitats in which habitat suitability changed between zero and one. Hence, performance of the habitat model demonstrates that it is able to assess different conditions properly. This point should be noticed in the further studies of environmental flow by the physical habitat method. In fact, the field studies should include a wide range of suitable and unsuitable habitats to develop a reliable habitat model.

Figure 8-2-8 displays the storage variations in the simulated period that indicates all of the algorithms are able to provide the minimum operational storage in the reservoir. In other words, it indicates that penalty functions could perform properly. However, the performance of algorithms is not the same in terms of storage variation in the reservoir that should be considered in the system performance analysis. Furthermore, Figure 8-2-9 shows optimal environmental flow regime by different algorithms that demonstrates performance of the used algorithms is different in terms of environmental flow optimization. In other words, it seems that using different evolutionary algorithms, measuring system performance and utilizing a decision-making system for selecting the best approach are necessary in the optimization of environmental flow regime.

Measuring system performance of the optimization system in terms of environmental flow supply needs to compare the physical habitat suitability in the optimal operation of the reservoir and the natural flow. Figure 8-2-10 displays average depth and velocity time series at the downstream river. The difference between the performances of the optimization algorithms could be observed in this figure as well. Figure 8-2-11 displays optimal average habitat suitability time series for all of the algorithms compared with habitat suitability by the natural flow. It sounds that the performance of algorithms are robust that means general performance of the evolutionary algorithms might be acceptable in terms of environmental flow optimization. However, the performance of some algorithms such as BA is not very robust in some time steps. In other words, they might not provide a sustainable ecological status for the downstream river. Accurate comparison of the results of the algorithms is not possible by observation. Thus, the system performance indices would be helpful to compare them.

Figure 8-2-12 displays system performance indices regarding habitat suitability for different algorithms including RI, VI and MAE. Based on this figure, RI indicates that some algorithms such as ASO,BA and GA are more reliable methods to optimize environmental flow regime. In contrast, IWO is the weakest method in terms of reliability index. It should also be noted that performance of GSA and DE are similar in terms of reliability index that means they might be robust methods for optimization of the environmental flow regime. VI indicates the performance of PSO and SFLA is slightly better than other algorithms. MAE indicates either IWO or BA is not robust methods to optimize environmental flow regime at downstream of the reservoir. To sum up, the performance of algorithms might be different because evolutionary algorithms are not able to guarantee the global optimization which means using different algorithms to find the optimal solution is recommendable.

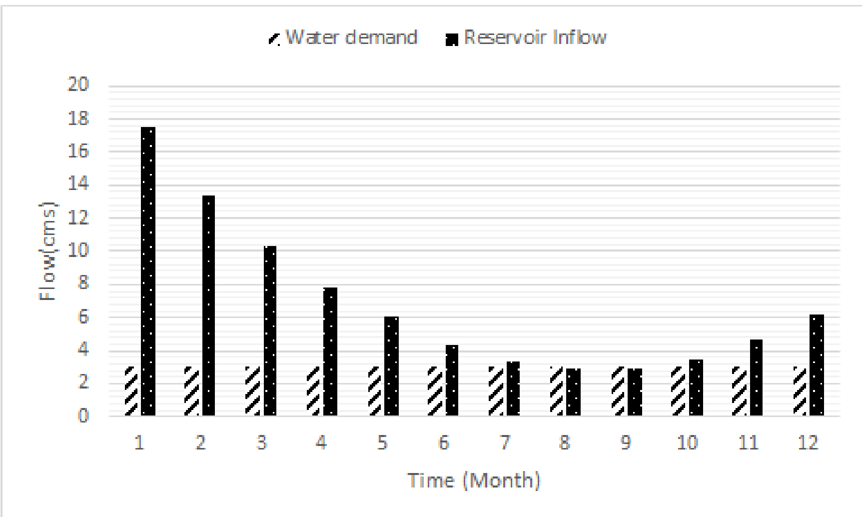



**Figure 8-2-4-Monthly inflow and demand of Latian dam as case study (May- April)**

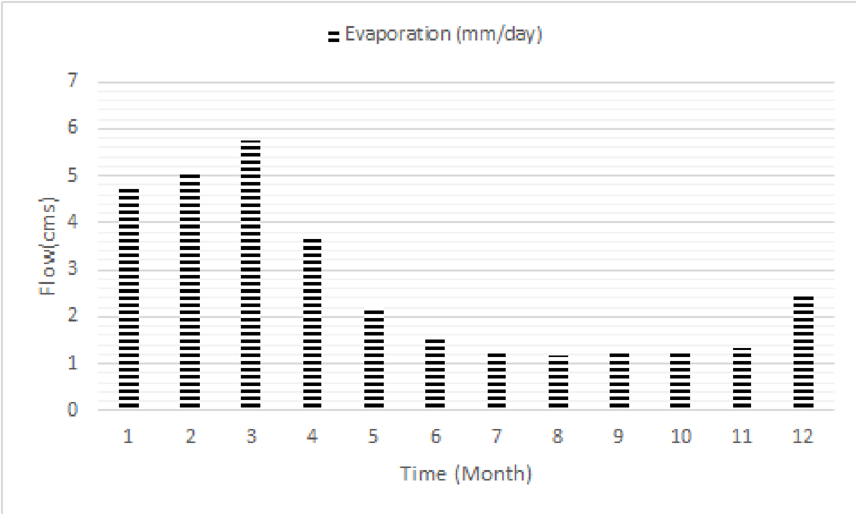



**Figure 8-2-5-Mean monthly evaporation from surface of Latian reservoir as case study (May-April)**

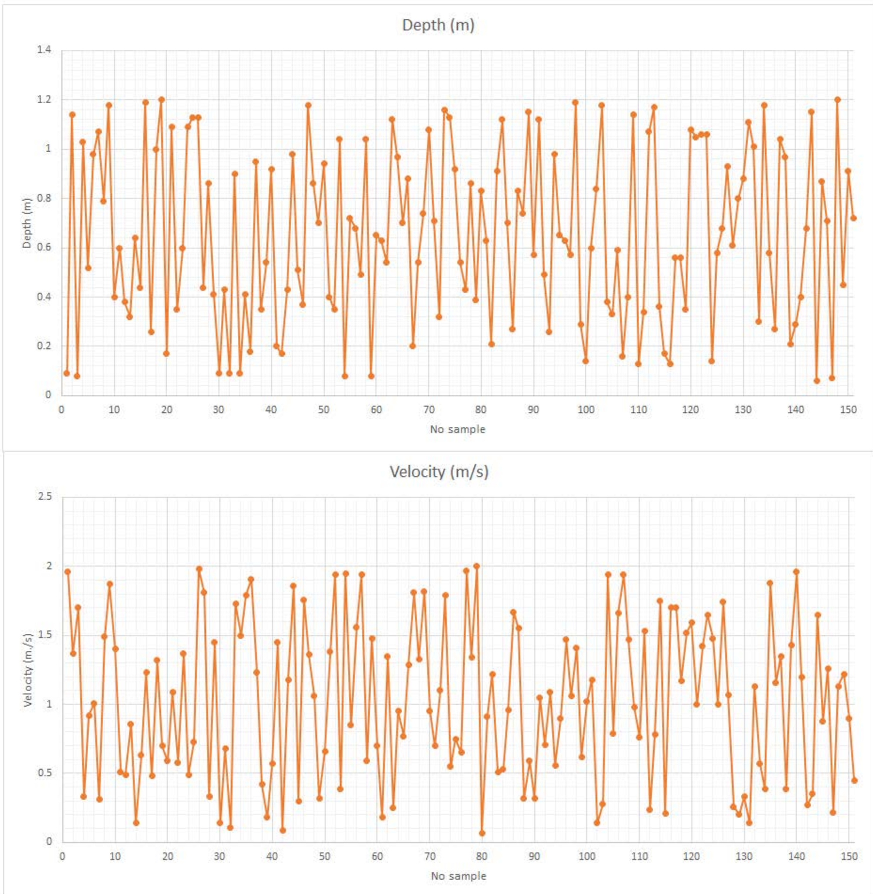



**Figure 8-2-6- Recorded depth and velocity in observed physical habitats for testing process of ANFIS based physical habitat model**

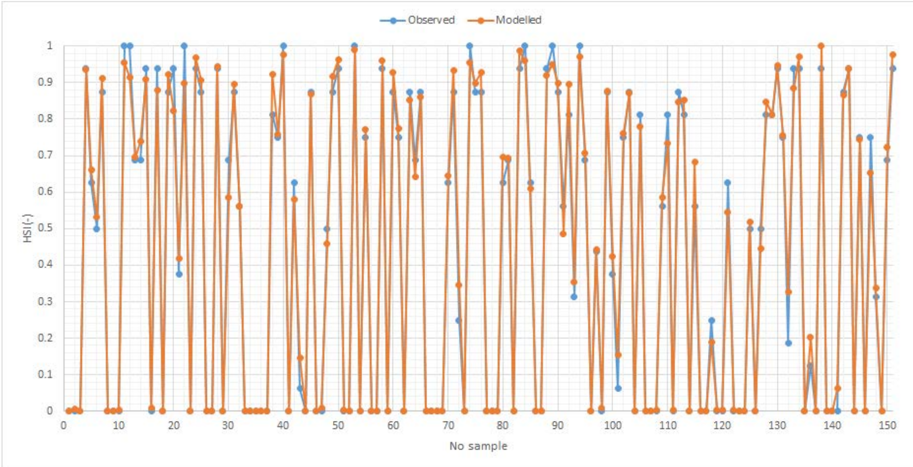



**Figure 8-2-7- Comparison of observed and simulated habitat suitability index in testing process of ANFIS based physical habitat model**

Analysing the optimization system in terms of habitat suitability is not sufficient. It is essential to measure system performance in terms of storage benefits as well. In other words, performance analysis of the optimization system in terms of storage loss demonstrates how the reservoir operation model is able to maximize storage benefits in the reservoir. Optimal storage in the reservoir is one of the main requirements for operation of reservoir such as optimal performance of hydropower plant. As presented in the previous section, optimal reservoir storage was considered 55 Mcm that is able to provide acceptable benefits for the Latian dam. VI and MAE were used to measure system performance in terms of storage loss that results are displayed in Figure 8-2-13. MAE for the storage loss demonstrates that GSA is a robust method to protect optimal storage in the reservoir. In contrast, other methods such as IWO and PSO are not appropriate methods to optimize storage of the reservoir. However, VI does not corroborate GSA as a robust algorithm in terms of storage benefits. In fact, DE is the best method in terms of vulnerability of the storage in the reservoir. In contrast, GSA, GA, IWO and SFLA are not robust methods in this regard. GSA generates the minimum mean absolute error compared with optimal storage. However, it might generate high vulnerability for the system.

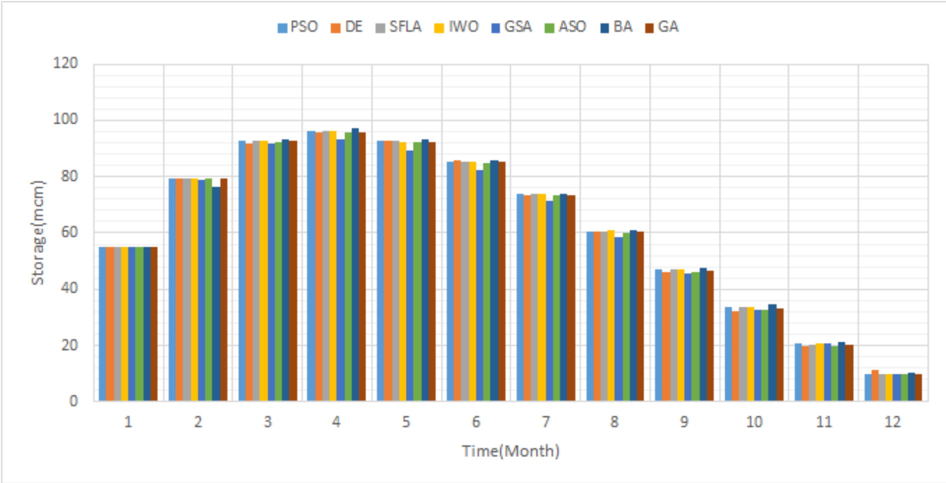



**Figure 8-2-8- Storage variation in the reservoir**

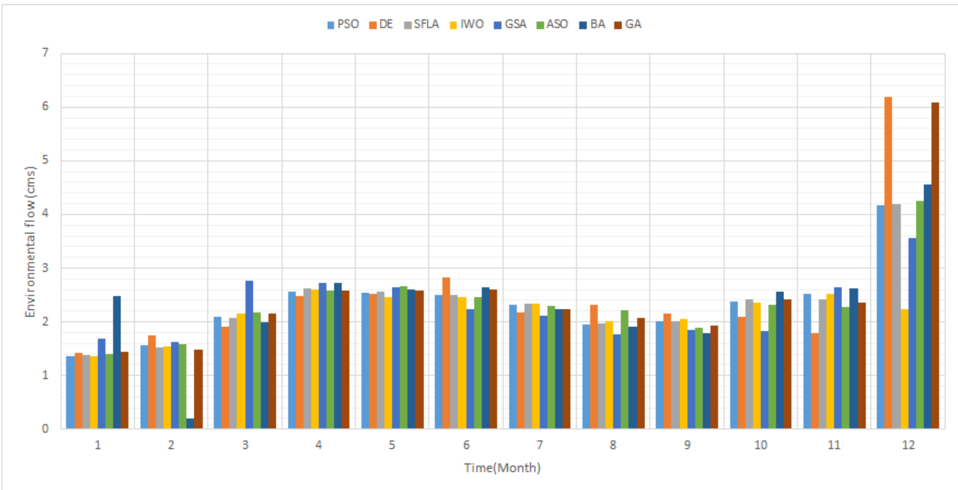



**Figure 8-2-9- Environmental flow regime optimized by different evolutionary algorithms**

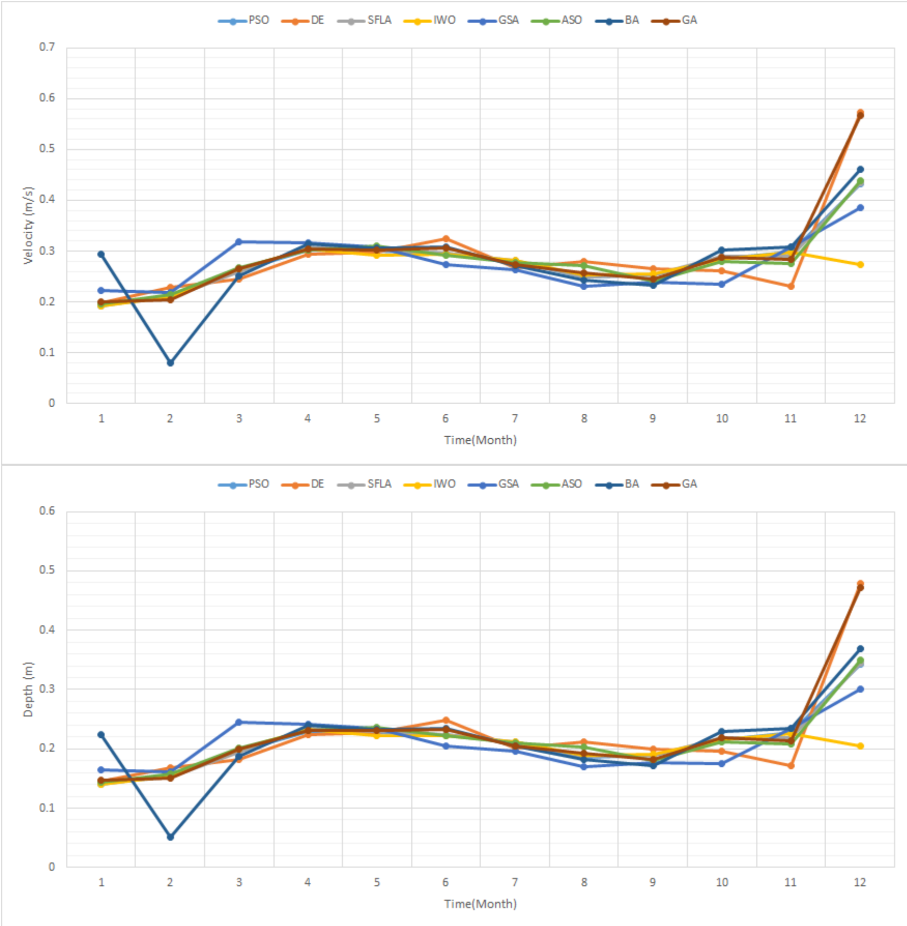



**Figure 8-2-10- Average depth and velocity at downstream river of reservoir due to environmental flow regime**


**Figure 8-2-11- Habitat suitability distribution by different algorithms compared with possible suitability by natural flow**

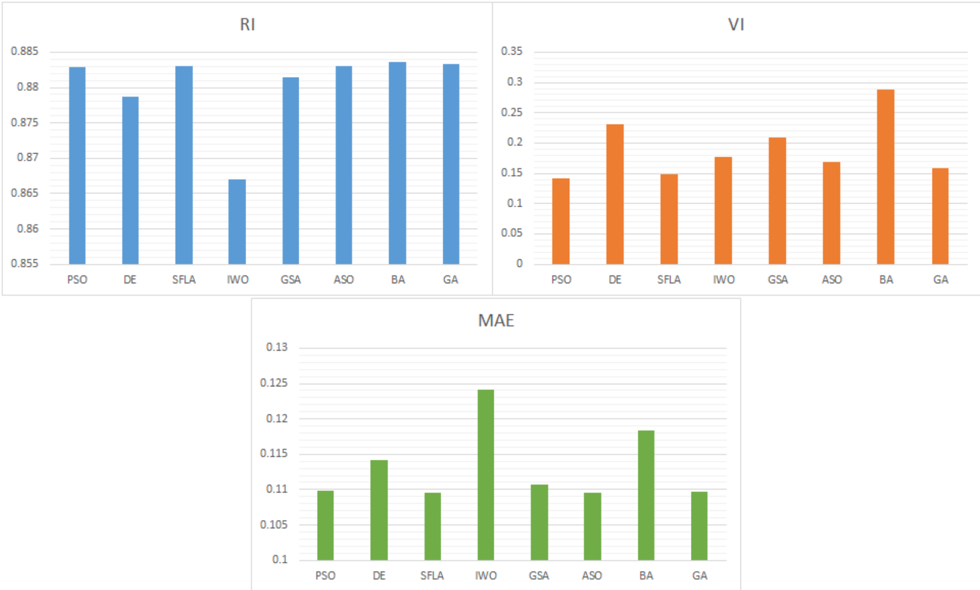



**Figure 8-2-12- System performance indices for release**


**Figure 8-2-13- System performance indices for storage**

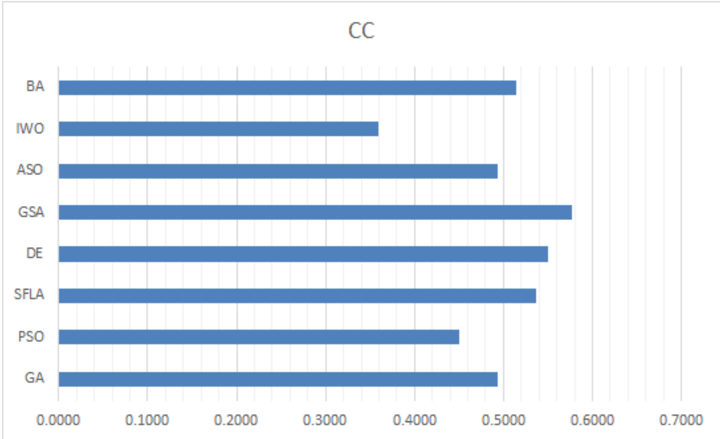



**Figure 8-2-14- Rank of different algorithms by FTOPSIS method**

According to the presented results, it seems that outputs of the different optimization algorithms are contradictory that means using decision-making system is necessary to select the best method and finalize optimal downstream environmental flow regime. As presented in the previous section, we applied FTOPSIS decision-making system to prioritize optimization algorithms. We utilized two decision makers in the development of the decision-making system who defined inputs of the FTOPSIS including weight of importance and rating of alternatives. Table 8-2-2 displays weight of importance for different algorithms. Based on this table, RI, VI and MAE of release were prioritized as medium (M), high (H) and very high (VH) respectively. It is required to discuss on how to allocate weight of importance for each criterion. Annual environmental flow is less important than monthly environmental flow. If the purpose of environmental is protection of river habitat it should be able to provide sufficient required flow for each month. Furthermore, VI was considered as high. Higher vulnerability might cause considerable damage to river habitats. MAE was considered as very high. It is able to indicate mean error of the physical habitat suitability by the optimization model for the simulated period. On the other hand, two criteria including VI and MAE were considered for storage loss of the reservoir. In fact, these criteria demonstrate robustness of the optimization system in terms of storage benefits. They prioritized as high and very high similar to vulnerability index and mean absolute error for environmental flow.

In the next step, rating of alternatives was carried out that is displayed in the table 8-2-3. It seems that opinions by decision makers are slightly different. However, discrepancies are not considerable. Final ranking of methods is displayed in the figure 8-2-14 that demonstrates some methods are more appropriate compared with others for optimizing reservoir operation in terms of environmental flow and storage. IWO is the weakest method for optimization by the proposed framework in this research work that might be excluded in the next studies of environmental flow optimization in the practical projects. Moreover, either PSO or ASO or SFLA is not robust to optimize downstream environmental flow of the reservoir. It should be noted that the performance of the optimization system might be changed by applying other environmental flow assessment methods. Hence, outputs of this research work are only reliable for using ANFIS based method of physical habitat simulation as the environmental flow assessment method. Future studies should be focused on the application of other environmental flow methods in the structure of the reservoir operation optimization.

**Table 8-2-2- Weight of importance for different criteria**

| | RI | VI | MAE |
|---|---|---|---|
| Release | M | H | VH |
| Storage | n/a | H | VH |

**Table 8-2-3- Rating of alternatives by decision makers (VP: very poor, P: poor, RP: relatively poor, F: fair, RG: relatively good, G: good and VG: very good)**

| | **RI (Release)** | | | | | | |
|---|---|---|---|---|---|---|---|
| | VP | P | RP | F | RG | G | VG |
| GA | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| PSO | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| SFLA | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| DE | 2 | 0 | 0 | 0 | 0 | 2 | 0 |
| GSA | 0 | 0 | 0 | 0 | 0 | 1 | 1 |
| ASO | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| IWO | 0 | 0 | 0 | 1 | 1 | 0 | 0 |
| BA | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| | **VI (Release)** | | | | | | |
| | VP | P | RP | F | RG | G | VG |
| GA | 0 | 0 | 1 | 1 | 0 | 0 | 0 |
| PSO | 1 | 1 | 0 | 0 | 0 | 0 | 0 |
| SFLA | 1 | 1 | 0 | 0 | 0 | 0 | 0 |
| DE | 0 | 0 | 0 | 0 | 0 | 1 | 1 |
| GSA | 0 | 0 | 0 | 0 | 1 | 0 | 1 |
| ASO | 0 | 0 | 0 | 1 | 1 | 0 | 0 |
| IWO | 0 | 0 | 0 | 1 | 1 | 0 | 0 |
| BA | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| | **MAE (Release)** | | | | | | |

| | VP | P | RP | F | RG | G | VG |
|---|---|---|---|---|---|---|---|
| GA | 1 | 1 | 0 | 0 | 0 | 0 | 0 |
| PSO | 1 | 1 | 0 | 0 | 0 | 0 | 0 |
| SFLA | 2 | 0 | 0 | 0 | 0 | 0 | 0 |
| DE | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| GSA | 1 | 1 | 0 | 0 | 0 | 0 | 0 |
| ASO | 2 | 0 | 0 | 0 | 0 | 0 | 0 |
| IWO | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| BA | 0 | 0 | 0 | 0 | 0 | 1 | 1 |
| | **VI (Storage)** | | | | | | |
| | VP | P | RP | F | RG | G | VG |
| GA | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| PSO | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| SFLA | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| DE | 0 | 0 | 0 | 0 | 0 | 2 | 0 |
| GSA | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| ASO | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| IWO | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| BA | 0 | 0 | 0 | 0 | 0 | 1 | 1 |
| | **MAE (Storage)** | | | | | | |
| | VP | P | RP | F | RG | G | VG |
| GA | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| PSO | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| SFLA | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| DE | 0 | 0 | 0 | 0 | 1 | 1 | 0 |
| GSA | 0 | 0 | 0 | 1 | 1 | 0 | 0 |
| ASO | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| IWO | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| BA | 0 | 0 | 0 | 0 | 0 | 1 | 1 |

Computational complexities should be discussed in the application of the evolutionary algorithms. Generally, it defines as the required time and memory to find the optimal solution. For example, high computational time might reduce efficiency of the algorithm in the numerous numbers of simulations or covering a long period of simulation. We compared algorithms in terms of computational time as well. GSA was selected as the best method in terms of computational time and required number of iterations. However, we recommend utilizing DE and SFLA algorithms for future applications of the proposed methods and finalizing downstream environmental flow regime of the reservoir by considering all of the technical issues. Required memory for the different algorithms was the same. Seemingly, the proposed structure is appropriate to maximize environmental benefits. However, considering other environmental challenges might be essential in a practical project. Other environmental factors such as water quality could be added to the proposed structure. The most important advantage of the proposed framework is to provide an optimal environmental flow that might reduce negotiations between environmental advocators and reservoir managers. The proposed framework is able to mitigate environmental impacts of the reservoir at downstream by considering physical habitat suitability as one of the most important environmental factors in the aquatic conservation.

As a summary of this section, we proposed a simulation-optimization framework to reduce downstream physical habitat loss and benefits of the reservoir by a coupled ANFIS- evolutionary optimization in which ANFIS based model assesses physical habitat suitability at downstream river and evolutionary algorithms optimize downstream environmental flow considering minimum and maximum defined storage in the reservoir. Depth and velocity were considered as the physical habitat parameters. Nine evolutionary algorithms were utilized to optimize environmental flow. Based on the results, the ANFIS based habitat model is robust to assess physical habitat suitability. Hence, it can be used as a component of the optimization model for the reservoir operation. Results indicate that performance of different evolutionary algorithms might be different in terms of reliability, vulnerability and mean absolute error of release for environment and storage. Decisions-making system demonstrated GSA is the best algorithm in the case study. SFLA and DE were ranked as the second and third appropriate algorithms for minimizing downstream physical habitat loss. Utilizing the proposed framework is helpful to optimize downstream environmental flow regime that might be finalized in the negotiations between environmental advocators and reservoir managers. The proposed framework might reduce negotiations due to considering requirements of the reservoir management and downstream aquatic habitats simultaneously.

## ***8.3 Using mesohabitat modeling for assessing environmental flow*** ***(Framework 3)***

### 8.3.1 Study area and problem definition

The southern Caspian Sea basin consists of many rivers and streams where have been recognized as the valuable habitats for many aquatic species. Tajan River is one of the most important rivers in this basin where is a proper habitat for many aquatics. Moreover, this river is responsible for supply of irrigation demand of downstream farms. In other words, supply of water for environment and irrigation demand is a challenge in this region. Rajaei dam has been constructed at the upstream of this river to supply water and electricity demands. On the one hand, regional department of environment (DOE) highlights lack of habitat suitability at downstream river reach as a serious concern for river ecosystem. On the other hand, regional water authority is concerned regarding benefits from the reservoir. Hence, design of an integrated optimization framework that is able to minimize all the losses might be essential for management of the reservoir in the future periods. Figure 8-3-1 displays the location of Tajan river basin, Rajaei dam and land use. Minimum operational storage, maximum possible storage and optimal storage in the reservoir are defined as 60, 160 and 140million cubic meters (MCM) in this research work respectively. Water demand time series at downstream for the reservoir is displayed in the figure 8-3-2. We considered that reservoir should be able to supply this demand as much as possible. Moreover, figure 8-3-3 displays evaporation from the surface of the reservoir. Evaporation is one of the required data for the optimization model.

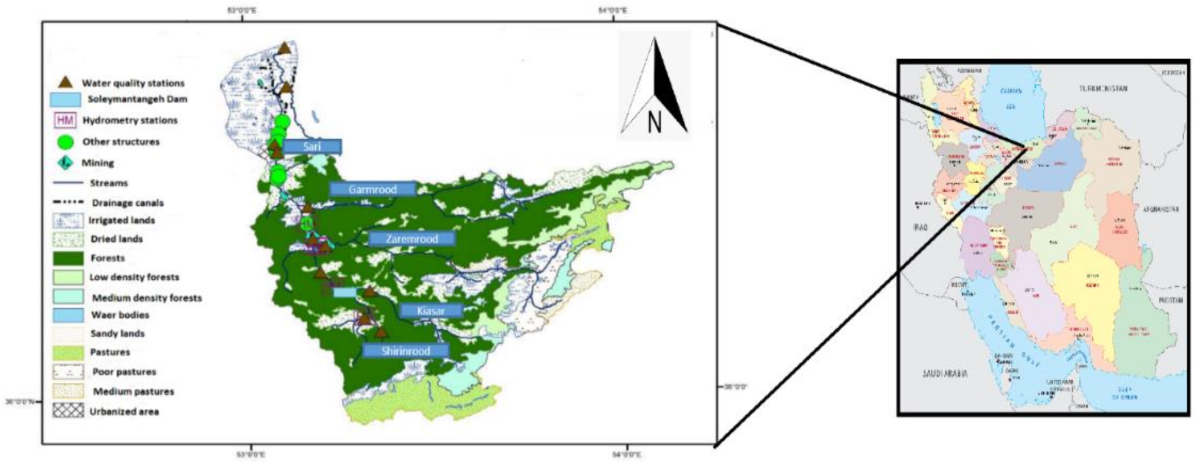



**Figure 8-3-1- Land use and river network map of Tajan basin**

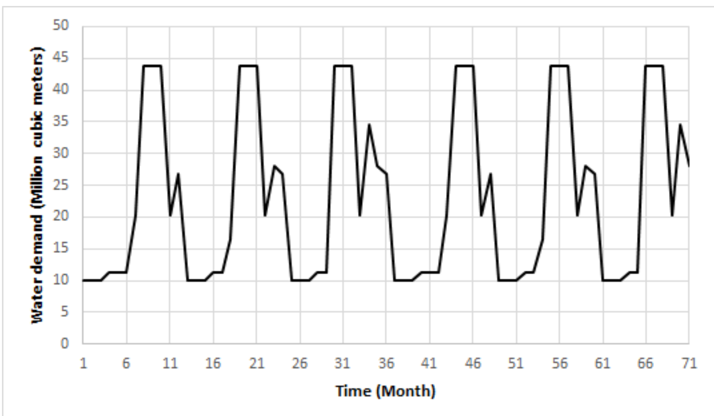


**Figure 8-3-2- Maximum water demand in the simulated period (6 years)**

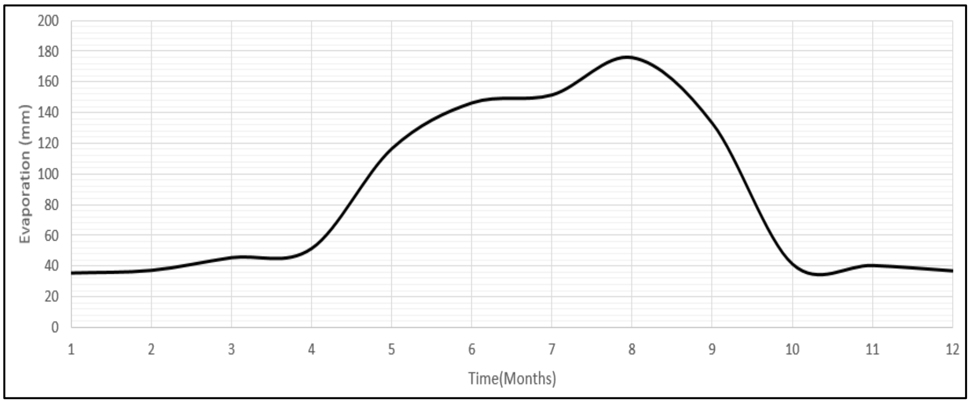



**Figure 8-3-3-Evaporation from surface of reservoir in different months (Jan to Dec)**

### 8.3.2 Mesohabitat modelling

We carried out velocity and depth measurements and subjective field studies in different cross sections of the river reach to recognize pools, riffles and runs. Then, developed criteria was combined with the results of 2D hydraulic simulation to assess area of pool, riffles and runs in each rate of flow. More details on mesohabitat modeling are presented as displayed in the Figure 8-3-4

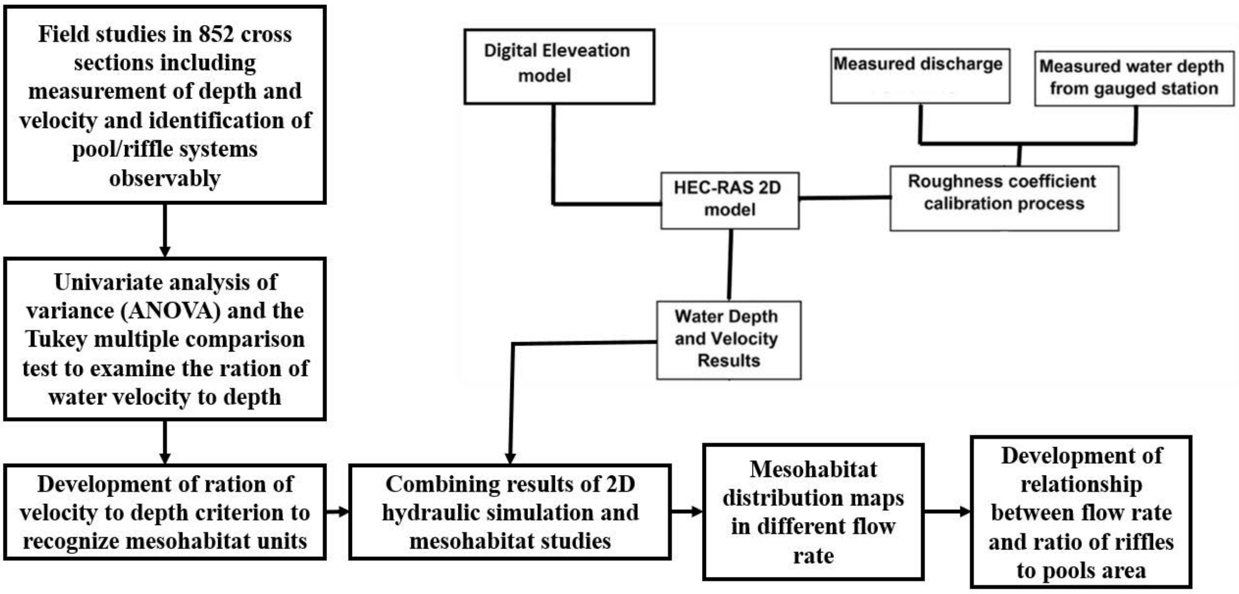



**Figure 8-3-4-Workflow of mesohabitat modeling in this research work**

Figure 8-3-4 indicates that final output of mesohabitat modeling is a relationship between area of mesohabitat units and flow rate. This relationship was utilized in the structure of optimization model to mitigate environmental impact of the reservoir at downstream. Structure of the optimization model is presented in the next section

### 8.3.3 Optimization model

Using an appropriate objective function is the basic need for developing a reservoir operation model. This objective function might be defined based on the requirements of the reservoir management. Two main purposes were considered in the initial objective function including minimizing the difference between water demand and release for demand and minimizing the difference between ratio of riffle to pool in the natural flow and environmental flow at downstream as displayed in the equation 1

$$\boldsymbol{OF} = \sum_{t=1}^{T}\left(\frac{D_t-R_t}{D_t}\right)^2+\left(\frac{NPR_t-OPR_t}{NPR_t}\right)^2 \tag{1}$$

where $D_t$ is target demand, $R_t$ is release for demand, $NPR_t$ and $OPR_t$ are natural ration of riffle and run areas to pool area in the natural status and optimal operation of the reservoir. As a description regarding NPR and OPR, they define environmental suitability at the downstream simulated river. A proper ratio of riffle plus run area to the pool area could be considered as the suitability index for the river habitats. NPR is suitability ratio in the natural flow and OPR is suitability ratio in the optimal operation of the reservoir. Minimizing the difference between these two values was considered as one of the purposes of the optimization model. Moreover, it is essential to add some constraints for reservoir operation optimization. Three constraints should be considered including constraint on the maximum storage, minimum operational storage and maximum water demand. Using constraints in the evolutionary algorithms might need a tricky method to insert the constraints in the structure of optimization model. Penalty function method is a smart solution that has widely been used in the previous reservoir operation studies. Hence, we applied this method in this research work. More details regarding the penalty function method have been addressed in the literature (Liang et.al, 2019). Equation 2 displays added penalty functions

$$\begin{cases} if S_i > S_{max} \rightarrow P1 = c1\left(\frac{S_t-S_{max}}{S_{max}}\right)^2 \\ if S_i < S_{min} \rightarrow P2 = c2\left(\frac{S_t-S_{min}}{S_{min}}\right)^2 \\ if\ R_t > D_t \rightarrow P3 = c3\left(\frac{R_t-D_t}{D_t}\right)^2 \end{cases} \tag{2}$$

where $s_{max}$ is maximum possible storage, $s_{min}$ is minimum operational storage, $s_t$ is storage in time step t and $D_t$ is demand in time step t. These penalty functions are added to the objective function for the optimization process. Equation 3 displays the final form of the objective function in this research work.

$$\boldsymbol{minimize(OF)} = \sum_{t=1}^{T}\left(\frac{D_t-R_t}{D_t}\right)^2+\left(\frac{NPR_t-OPR_t}{NPR_t}\right)^2 + P1_t + P2_t + P3_t \tag{3}$$

Furthermore, storage should be updated in each time step t, Equation 4 was utilized to update storage in each time step.

$$S_{t+1} = S_t + I_t - R_t - E_t - F_t - \left(\frac{EV_t \times A_t}{1000}\right), t = 1, 2, \ldots, T \tag{4}$$

where $S_t$ is storage at time period t, $I_t$ is inflow to reservoir at time t, $EV_t$ is evaporation from reservoir surface at time t, A is area of reservoir surface, $R_t$ is release for demand and $E_t$ is release for environment and $F_t$ is overflow. T is the time horizon. Overflow is calculated based on the equation 5.

$$\begin{cases} if\left(S_t + I_t - \left(\frac{EV_t \times A_t}{1000}\right)\right) \geq S_{max} \rightarrow F_t = S_t + I_t - \left(\frac{EV_t \times A_t}{1000}\right) - S_{max} \\ if\left(S_t + I_t - \left(\frac{EV_t \times A_t}{1000}\right)\right) < S_{max} \rightarrow F_t = 0 \end{cases} \tag{5}$$

It is required to explain how the overflow was defined in the operation of the reservoir in this research work. Overflow was considered as the release to the downstream of the reservoir. In fact, water supply is directly being pumped from the reservoir and overflow and environmental flow are released to the downstream. Hence, the treatment method in this research work is consistent with the water balance of the reservoir system.

Defining water demand and other factors in the optimization system should be explained as well. In the case study, agriculture was the main economic activity and the source of water consumption. In other words, reservoir has considerable role for supply of irrigation demand. The maximum water demand was defined based on the maximum irrigation demand at downstream agricultural lands proposed by the regional agricultural authority. Moreover, minimum operational storage was defined based on the recommendations by the regional water resources engineers who were responsible for management of the reservoir (Minimum operational storage was considered 60 MCM). The capacity of the reservoir (160 MCM) was defined based on the technical report of the dam as the maximum storage in the optimization model.

Another question is how the NPR and OPR were computed in the optimization system? NPR and OPR were calculated based on the R/P function (presented in the results and discussion) as the output of the mesohabitat modeling in which river flow is input and the R/P is the output of the function. R/P in the natural flow could be defined as the NPR and R/P in the optimal release could be considered as the OPR in each time step.

### 8.3.4 Metaheurtistic algorithms

We utilized four evolutionary algorithms including invasive weed optimization, particle swarm optimization (PSO), differential evolution algorithm (DE) and biogeography-based optimization (BBO) to optimize reservoir operation in this research work. More details on these algorithms are available in chapter 3.

### 8.3.5 System performance measurement

Each optimization system needs some indices to measure the robustness of performance. Three issues including supply of water demand, storage loss and mesohabitat loss must be taken into account for measurement of the performance in this research work. We applied reliability index to measure the robustness of the optimization model in terms of water supply due to possibility of secondary storage in the farms. In other words, if an optimization solution is able to maximize reliability of water supply, it will be the best solution. Equation 6 displays mathematical form of the reliability index for water supply.

$$\boldsymbol{Reliability\ index} = \frac{\sum_{t=1}^{T} \boldsymbol{R_t}}{\sum_{t=1}^{T} \boldsymbol{D_t}} \quad (6)$$

Moreover, it is essential to measure the system performance in terms of storage loss. Root means square error is an applicable index to measure storage loss in the reservoir. It is able to calculate mean error for actual storage compared with optimal storage. Furthermore, we applied root mean square error to measure system performance in terms of mesohabitat areas. Moreover, RMSE was used to measure robustness of performance in terms of water supply as secondary measurement index. Mathematical form of RMSE is displayed in equation 7 for water demand. Equation 8 displays RMSE for storage as well as equation 9 for mesohabitat units. Optimal storage used in the measurement index is a predefined storage level based on the recommendations by the water authority as the optimal value for the storage in the reservoir. In fact, deviation from the optimal storage might increase the storage loss in the reservoir.

$$\boldsymbol{RMSE_R} = \sqrt{\sum_{t=1}^{T} \frac{(\boldsymbol{D_t} - \boldsymbol{R_t})^2}{\boldsymbol{T}}} \quad (7)$$

$$\boldsymbol{RMSE_R} = \sqrt{\sum_{t=1}^{T} \frac{(\boldsymbol{Optimal\ storage} - \boldsymbol{s_t})^2}{\boldsymbol{T}}} \quad (8)$$

$$\boldsymbol{RMSE_R} = \sqrt{\sum_{t=1}^{T} \frac{(\boldsymbol{NPR_t} - \boldsymbol{OPR_t})^2}{\boldsymbol{T}}} \quad (9)$$

### 8.3.4 Results and Discussion

In the first section of the results and discussion, results of mesohabitat modeling are presented including results of hydraulic simulation, mesohabitat criteria and combining results of hydraulic simulation and mesohabitat field studies. Figure 8-3-5 displays the verification results of the hydraulic model in terms of simulating depth and velocity in the simulated river reach. It seems that the model is robust to simulate hydraulic parameters due to the limited difference between the simulated parameter and observed parameter. Figures 8-3-6 and 8-3-7 display the velocity and depth distribution in the representative downstream reach simulated by HEC-RAS 2D at flow rate of 30.05 $m^3$/sec. It should be noted that these figures are final simulated depth and velocity after verification process. Velocity changes indicate that flow velocity at upstream of reach is lower than downstream. In other words, velocity is increased toward the downstream. However, depth changes indicate that depth is reduced toward the downstream. The difference between hydraulic status at upstream and downstream demonstrates that types of mesohabitats might be different. Table 8-3-1 shows result of development of criteria to identify mesohabitats based on described methodology in the figure 8-3-4.

**Table 8-3-1- Developed criteria for identification of pools, runs and riffles**

| Mesohabitat type | Pool | Run | Riffle |
|---|---|---|---|
| **Ratio velocity to depth** | V/D<0.65 | 0.65-4.64 | 4.64<V/D |

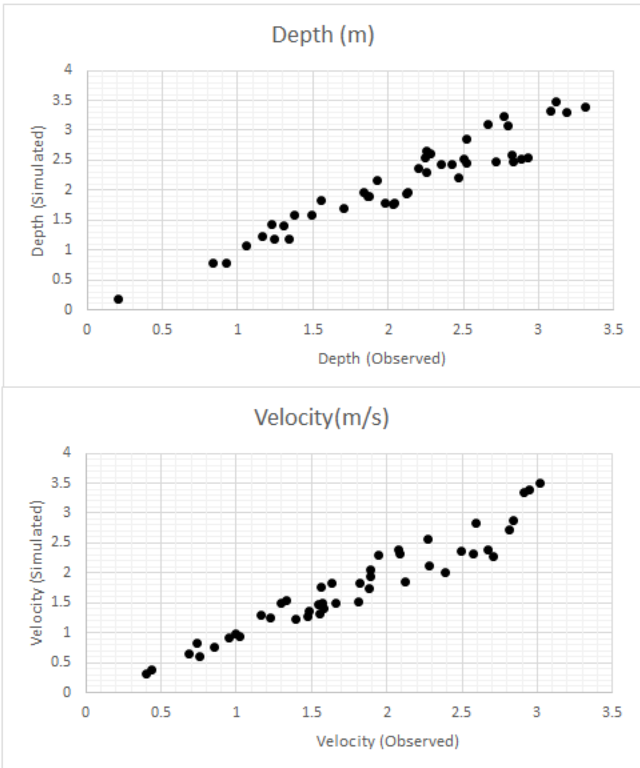



**Figure 8-3-5- Verification results of the hydraulic simulation at the downstream river reach**

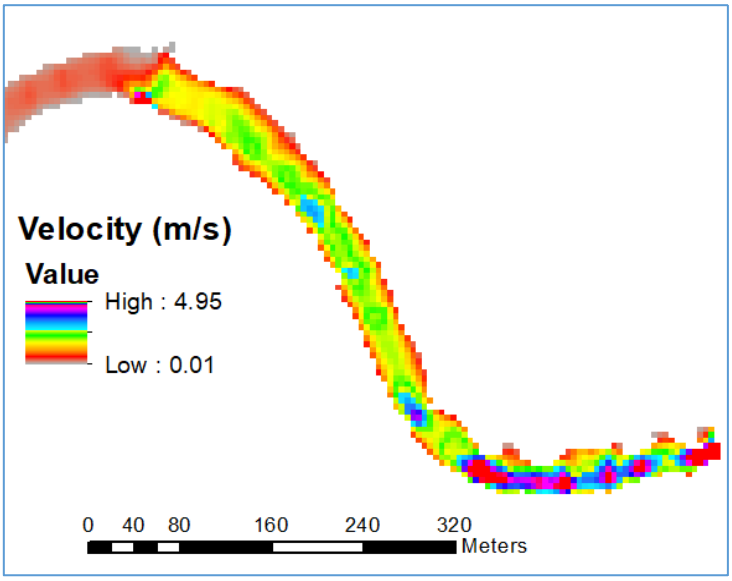



**Figure 8-3-6- Velocity changes resulted by hydraulic simulation at flow rate of 30.05 m$^3$/sec as sample of hydraulic simulation results in the simulated downstream reach**

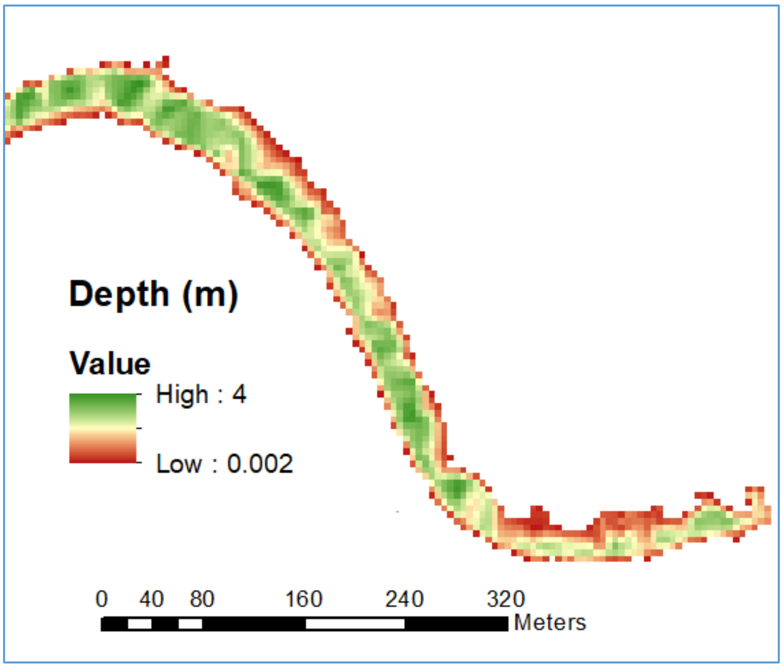



**Figure 8-3-7- Depth changes resulted by hydraulic simulation at flow rate of 30.05 m$^3$/sec as sample of hydraulic simulation results in the simulated downstream reach**

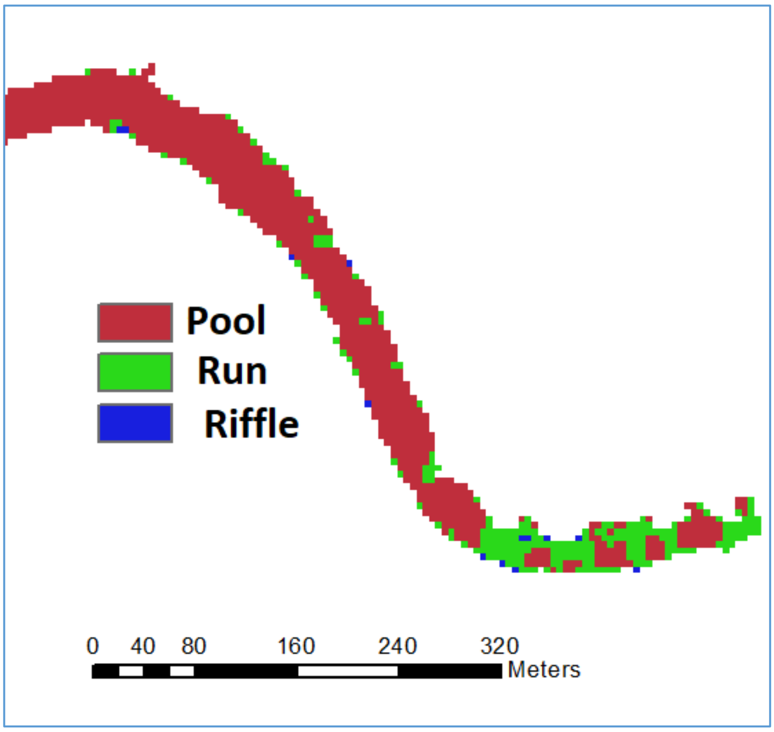



**Figure 8-3-8- Mesohabitat map resulted by described methodology in the figure 4 at flow rate of 30.05 m$^3$/sec as sample of hydraulic simulation results in the simulated downstream reach**

Figure 8-3-8 displays microhabitat map based on combining result of field studies and hydraulic simulation in the GIS environment. Initial habitat survey in the representative reach demonstrated that most of habitats are pools due to bed particle size and slope of the river. We considered role of run and riffle as the same in this research work. In other words, runs and riffles have the same biological role to protect suitability of river habitats. Protecting riffle or run habitats in the simulated reach is vital that means lack of sufficient runs or riffles might be effective to reduce possibility of biological activities such as searching for food. For example, some fishes might use the macroinvertebrates and insects that are considerably available in the riffle or run habitats. In other words, lack of availability of riffles or runs might reduce the potential food for the fishes. In fact, the fishes have the movement between riffle and pools that is a requirement for a sustainable ecological status of the river ecosystem. Hence, the main objective of the simulation-optimization method is to minimize the difference between ratio of run and riffle areas to pool areas (R/P) in the natural flow and optimal release from the reservoir. Relationship between flow and R/P is displayed in the Figure 8-3-9. It seems that general trend of developed relationship demonstrates that area of run and riffle will enhance by increasing rate of flow. This relationship was utilized in the optimization model directly.

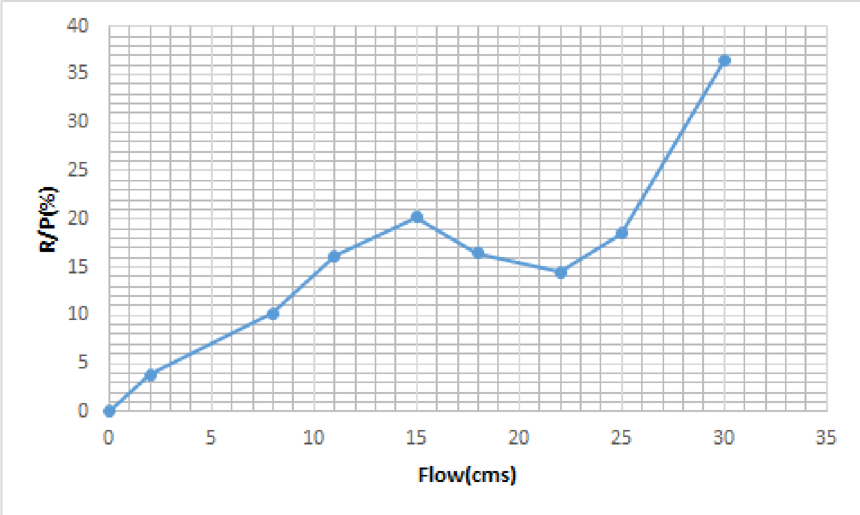



**Figure 8-3-9- Final relationship between flow rate and R/P applied in the reservoir operation optimization (Flow in cubic meters per second)**

In the second section, we discuss on the optimization results as the main outputs of this research work. First, it is essential to present direct outputs of reservoir operation optimization. Figure 8-3-10 displays release for demand by different evolutionary algorithms in the optimization model. As presented in the previous section, reservoir will not be able to supply maximum demand for the agriculture at downstream area that means other water resources such as ground water might be useable. However, target of optimal reservoir operation is to supply maximum demand by the reservoir as much as possible. Results of the optimization demonstrates that performance of different algorithms might be different in terms of water supply. In other words, it seems that RMSE of water supply for some algorithm is considerable. Moreover, the reliability of water supply was considered in the system performance measurement. Based on the results, the optimization model is able to consider the constraints in the optimization process that means the performance of the penalty function method is reliable. As can be observed, release is not more than maximum requested water demand in all the simulated months.

Figure 8-3-11 displays storage in the simulated period for different evolutionary algorithms. Some points must be noted in this regard. First, some algorithms such as DE estimates more storage in many time steps compared with other algorithms such as PSO. It should be considered as a major point in the optimization model due to importance of storage in the reservoir. Hence, it seems that performance of algorithms might directly affect benefits from the storage in the reservoir. In other words, results of storage optimization indicate that using different algorithms is necessary to evaluate performance of reservoir operation optimization. It is more essential in cases such as developed optimization model that is a complex operation model. In fact, the optimization of reservoir operation in terms of water supply, storage and environmental impacts should simultaneously be considered. Performance of minimum operational storage penalty function should be discussed. Robust performance of penalty function could be observed in the storage time series. Minimum storage in all the algorithms is very close to 60 MCM as the minimum operational storage defined by water authority, which has been considered in the optimization model. Moreover, performance of maximum storage penalty function is perfect. The maximum storage in the simulated period in all of the time steps is not more than maximum possible storage in the reservoir.

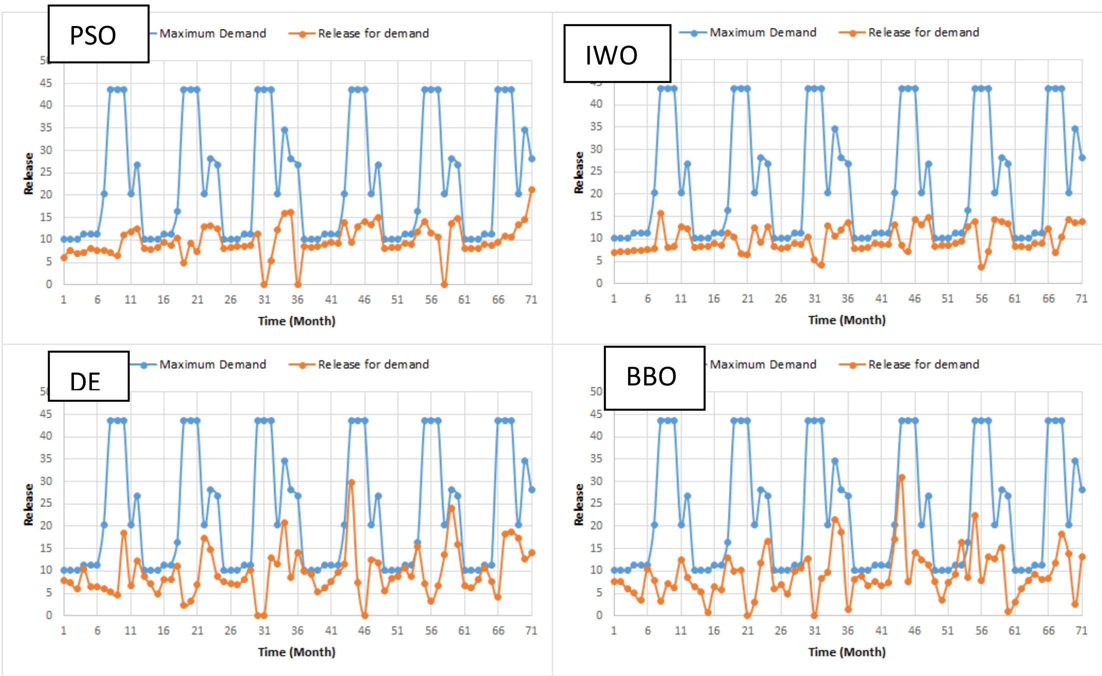



**Figure 8-3-10- Optimal release for water demand by different optimization algorithms (Million cubic meters)**

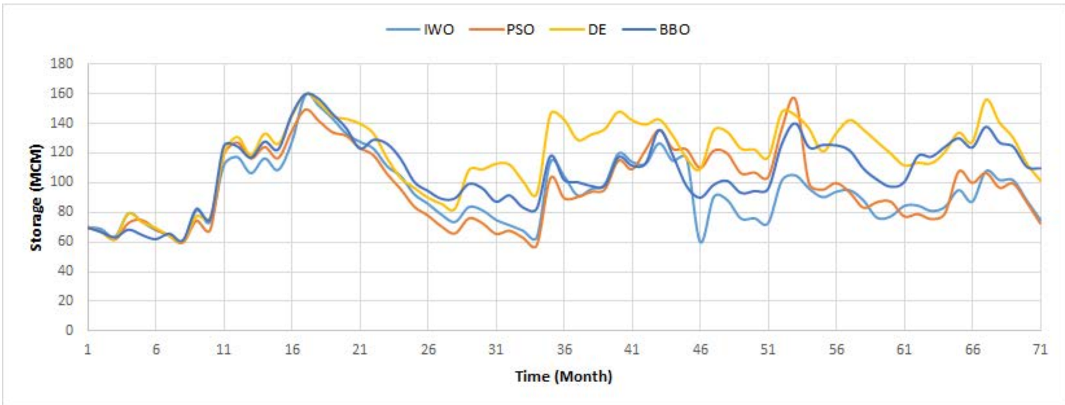



**Figure 8-3-11- Optimal storage for water demand by different optimization algorithms**

Assessing mesohabitats should be carried out based on R/P (%) in the optimal operation compared with natural condition. Figures 8-3-12 to 8-3-15 display R/P (%) time series in the simulated period for different evolutionary algorithms. It seems that the performance of algorithms is not similar in terms of mesohabitat units. However, more discussion on the results is not possible without computing measurement indices. It is required to explain how R/P (%) can be used for assessing the optimization model in terms of environmental suitability. In fact, if the optimization algorithm is able to minimize R/P in the natural flow and the optimal release, it might be more robust in terms of providing environmental suitability at downstream river of the reservoir. In other words, the natural flow might provide a sustainable environmental condition in the river ecosystem in terms of ecological status of the mesohabitats. In the optimization model, the purpose is to provide the R/P like the natural flow. However, it might not be possible due to needs for supply of water demand in practice. Thus, minimizing the difference between R/P in the natural flow and optimal release was considered as the purpose in the optimization system.

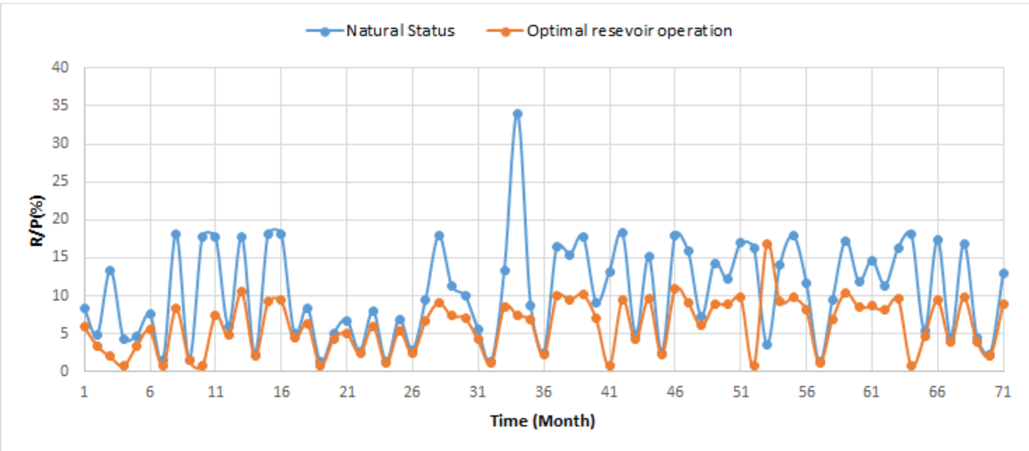



**Figure 8-3-12- R/P at optimal release and natural flow in the simulated period by PSO**

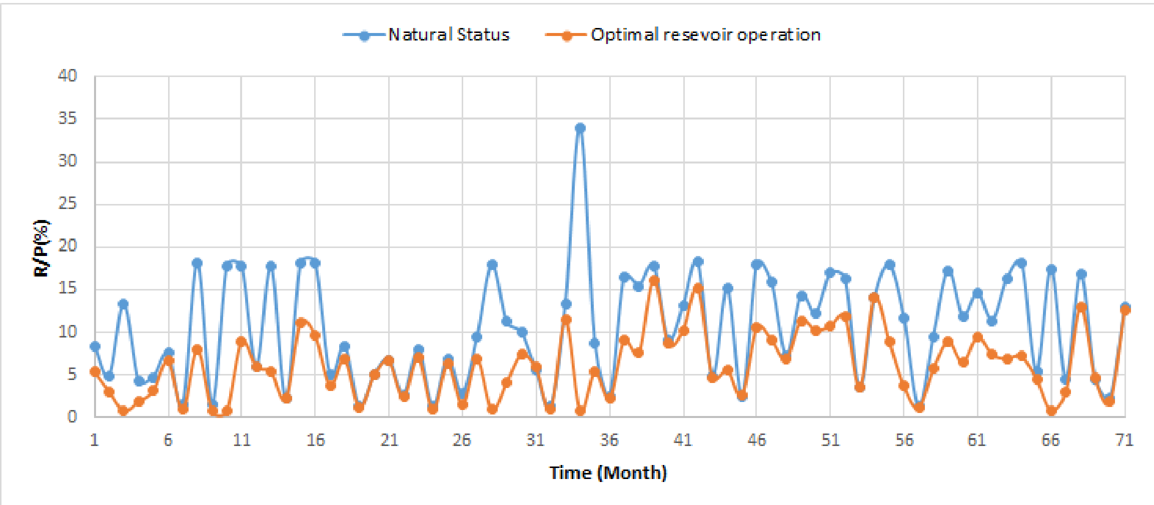



**Figure 8-3-13- R/P at optimal release and natural flow in the simulated period by DE**

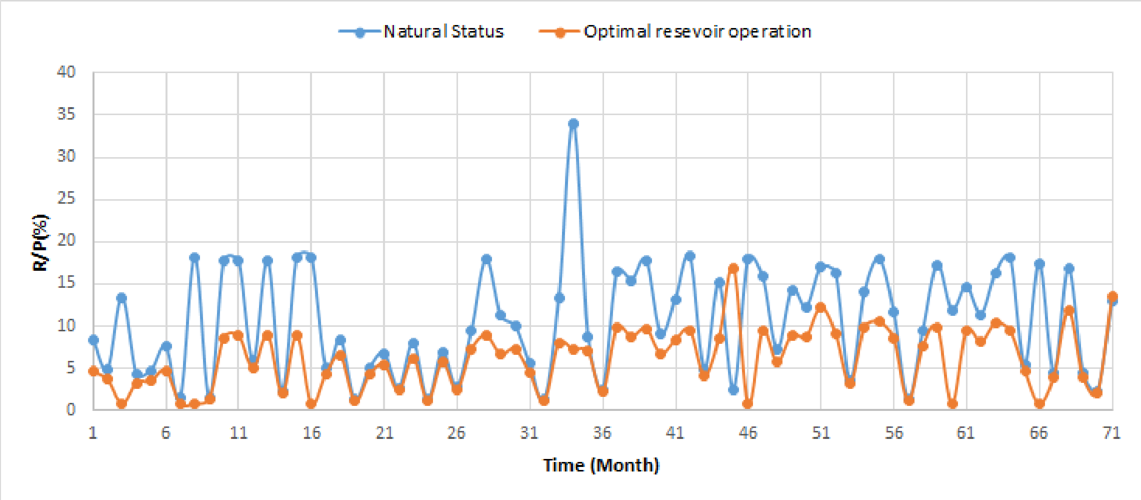



**Figure 8-3-14- R/P at optimal release and natural flow in the simulated period by IWO**

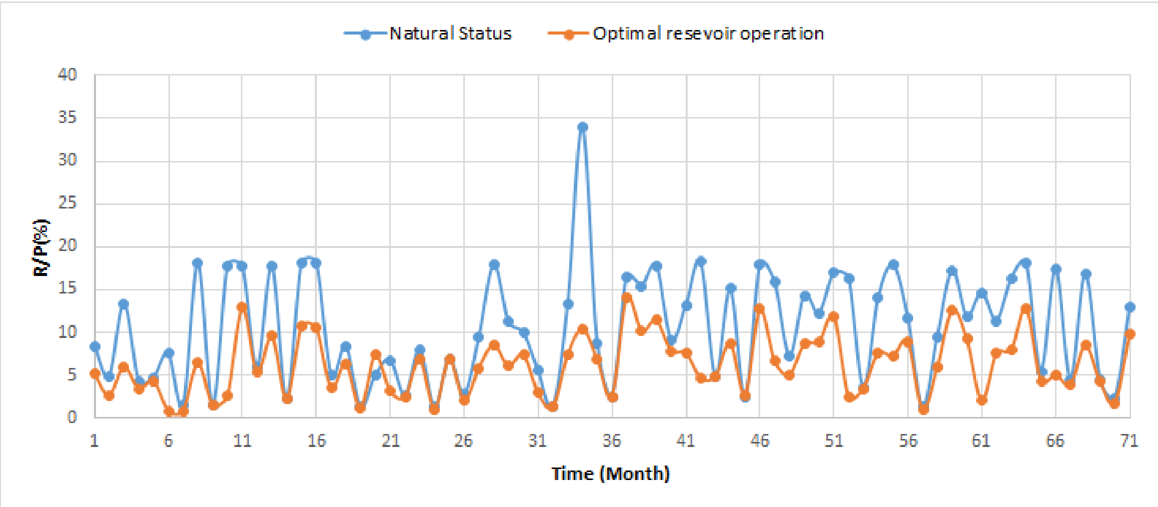



**Figure 8-3-15- R/P at optimal release and natural flow in the simulated period by BBO**

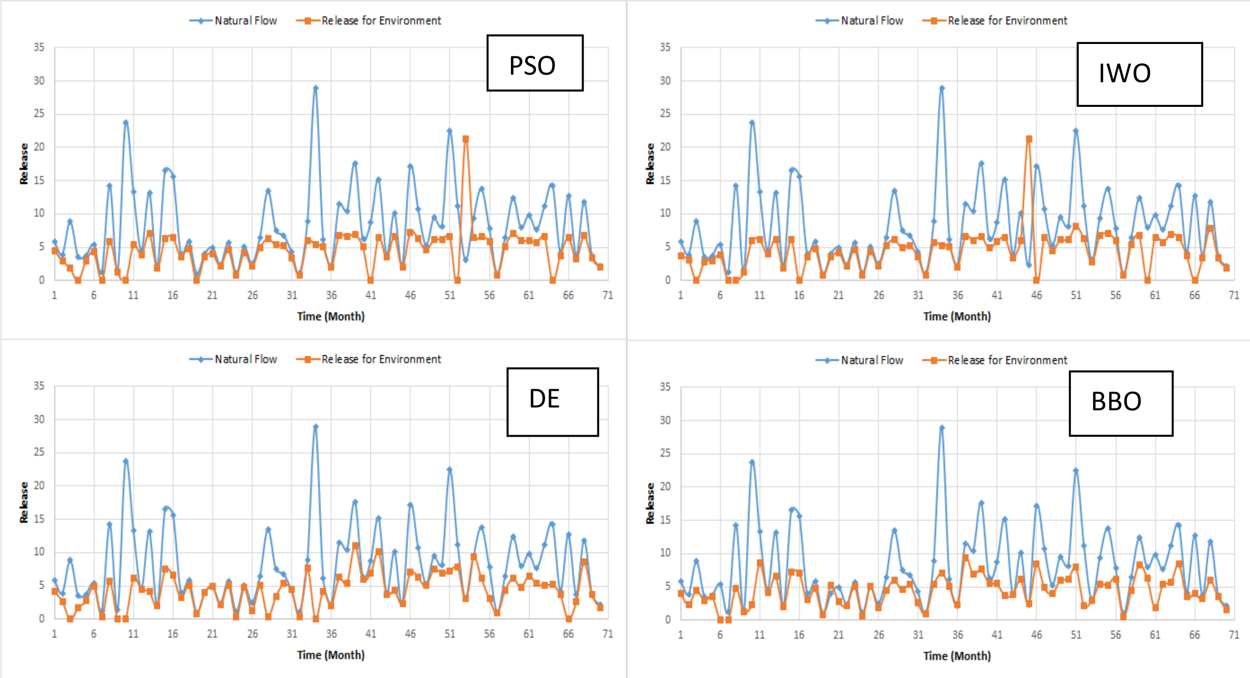



**Figure 8-3-16- Optimal release for environment by different optimization algorithms (Million cubic meters)**

Figure 8-3-16 displays release for environment based on the simulated mesohabitat modeling. According to the results, each algorithm proposes different release for environment in the simulated period. However, there are some similarities between algorithms. More discussion on results needs using measurement indices. Figure 8-3-17 displays the calculated RMSE for water demand, mesohabitats (Pool/Riffle systems) and storage. It should be noted that their units are not the same. In other words, unit for RMSE is the same with the original parameter for calculation. The first point is robust performance of algorithms in terms of mesohabitat units as the main purpose of this research work. In fact, results demonstrate that RMSE for Pool/Riffle system is 8% approximately. Hence, optimization process could reduce the differences between natural flow and optimal release for environment in terms of mesohabitat suitability. In other words, environmental impact is mitigated in the case study. A balance between mesohabitat areas compared with natural flow helps river ecosystem to protect biological activities of inhabitants. The proposed environmental flow is able to protect the diversity of mesohabitats. In fact, the proposed flow improves suitability of the river habitats compared with conventional reservoir operation optimization. For example, if runs or riffles have significant role for nutrition, their areas must be close to natural status. The proposed optimal release demonstrates that the difference between area of riffles and runs in an optimal release and natural flow are close. Hence, biological role of these habitats would be protected for all the species. It should be noted that mesohabitats might have biological role for all the species including fishes and benthos. Most of ecological environmental flow methods such as physical habitat simulation are based on target species. It might rise uncertainties regarding suitability of environmental flow for other species because using target-based method is not able to support needs of other species. However, using environmental flow methods for different species is not possible practically due to need for considerable field studies including abiotic parameters measurement and biological sampling. In other words, we need inexpensive methods to assess environmental flow at downstream of the reservoirs. This issue is very important especially in the developing countries due to lack of sufficient budget for environmental studies. However, an inexpensive method should be reliable. It should be able to support all the species based on ecological needs. The most important advantage of the proposed method is low cost and high reliability for different species. We do not claim that proposed method is the most reliable available method. However, it is able to assess environmental flow based on average suitability for all of the species.

Another advantage of using mesohabitat modeling is possibility of linking to reservoir operation model. In fact, if an environmental method is not able to be linked with the reservoir optimization model, it will not be reliable for practical applications. One of the challenges in the assessment of environmental flow is absence of ability to integrate benefits from the reservoir with environmental flow method. In other words, it is a challenge in the negotiations between stakeholders and environmental advocators. Stakeholders might believe that environmental flow might considerably reduce the benefits. The proposed method in this research work is able to minimize negotiations between stakeholders and environmental advocators. In fact, it is a multipurpose method to optimize reservoir operation in terms of benefits and environmental impacts. However, reduction of benefits and environmental impact are inevitable.

RMSE for release of water demand indicates that performance of all algorithms is similar. The differences between optimal release for demand could be observed based on the plotted time series. However, closeness between mean error of the algorithms demonstrates that their performance is similar approximately. Figure 8-3-17 displays reliability index of water demand for comparing algorithms. As presented in the previous section, reliability of supply of water demand should be noted as a key factor for the reservoir operation. The main responsibility of the reservoir is supply of irrigation demand in the case study. It should be noted that Rajaie reservoir is not the only water resource for defined ater demand in this research work. Hence, measuring reliability of water supply would be helpful to assess how much water demand could be supplied by the reservoir. Figure 8-3-18 displays that reliability for all of the algorithms is less than 50% which means role of other alternatives for supply of water demand is significant. Results demonstrate that either PSO or IWO has the same reliability for supply of water demand. Either DE or BBO slightly has lower reliability. The difference between algorithms is negligible.

Moreover, it is required to investigate the performance of algorithms in terms of storage by RMSE index. Figure 8-3-17 demonstrates that DE is the best method regarding storage benefits in the reservoir. Either PSO or IWO are the weakest methods in terms of storage benefits. It seems that DE is the best method for the reservoir operation optimization in this research work. The performance of algorithms is very similar in terms of water demand and mitigation of environmental impacts. However, there is slight difference between methods in terms of storage benefits. Hence, DE is the best method to optimize reservoir operation. It has the lowest RMSE for the storage benefits. We recommend using proposed method in the future reservoir operation studies in which reducing environmental impact at downstream river habitats is targeted. In fact, proposed method is able to minimize negotiation between stakeholders and environmental advocators.

The proposed method might be effective on the improvements of the environmental degradation at downstream of the reservoirs. In fact, the conventional method of the optimization in which the environmental flow is not considered in the structure of the optimization might not be able to manage the environmental degradations at downstream properly. The conventional methods such as hydrologic desktop method might consider a constant flow as the environmental flow at downstream of the reservoir without considering dynamic assessment of the mesohabitats in the structure of the optimization model that might be important in the biological activities of the aquatics. For example, some aquatics need to move to the riffles to search the food or to pools as the shelters. Previous methods of the reservoir operation optimization are not able to consider these ecological complexities in the management of the flow. However, the proposed method is able to link the water management in the reservoir system and the ecological management of the river in an integrated framework. In other words, the proposed method might be able to improve the ecological status of the river ecosystem that is remarkably advantageous compared with the conventional operation models in which ecological assessment is not considered in the optimization framework.

As a summary of this section, we proposed a linked mesohabitat model-reservoir operation optimization method to simultaneously reduce environmental impact at downstream river habitats and maximize benefits from the reservoir. Based on results, the proposed method is able to mitigate mesohabitat suitability loss. In other words, the difference between mesohabitat suitability in the natural flow and optimal release is minimized. Moreover, the results demonstrate that environmental requirements might reduce the reliability of water supply considerably. Differential evolution algorithm was the best method to optimize reservoir operation in this research work. The main advantage of the proposed framework is reduction of negotiation between stakeholders and environmental advocates due to mitigating environmental impacts and reservoir operation losses simultaneously.

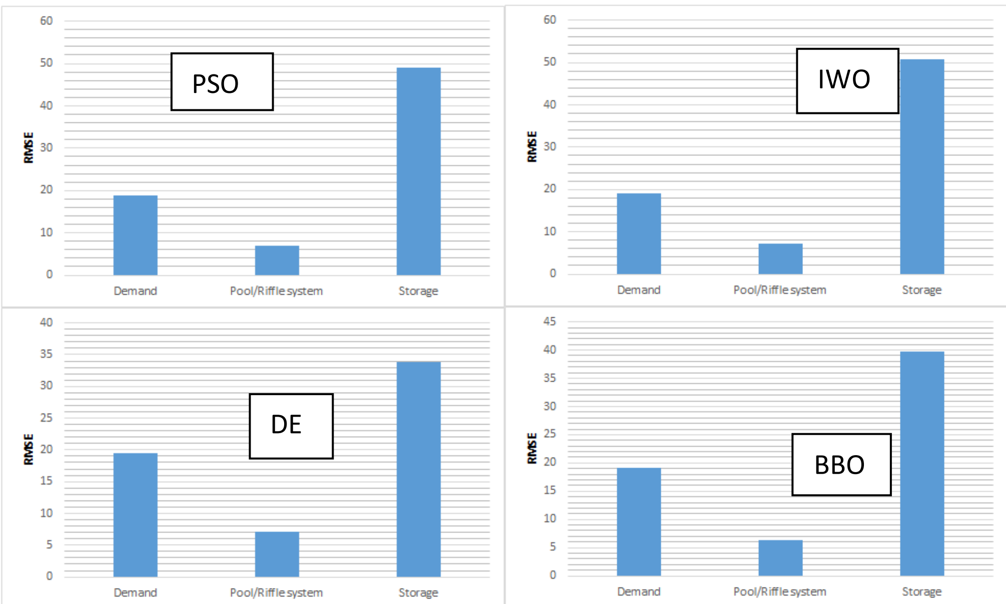



**Figure 8-3-17- RMSE for different algorithms in terms of water supply, mitigation of environmental flow and storage loss**

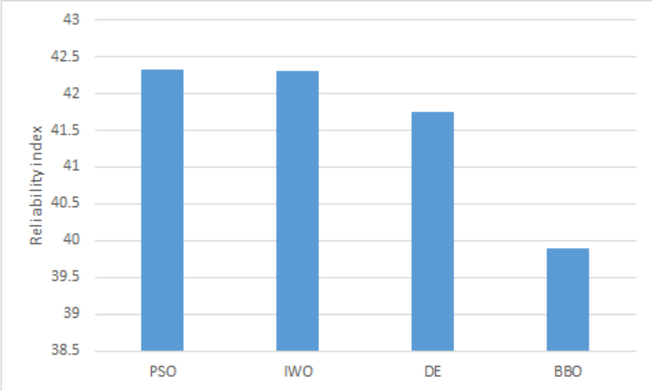



**Figure 8-3-18- Reliability index of water supply for different algorithms**

## ***<u>8.4 Using environmental flow model in flood mitigation by reservoirs</u> (Framework 4)***

### 8.4.1 Overview on the methodology

Our method mainly contains three sections including the flood assessment model, environmental flow assessment method and reservoir operation optimization. In other words, we put the outputs of the two first sections in the optimization model to finalize release for water demand and release to the downstream. Then, the performance of the outputs is measured in terms of system performance to demonstrate the robustness of the developed system. More details regarding each section are described in the following sections. Moreover, a description on the case study is available in this part as well.

### 8.4.2 Flood assessment model

Different approaches could be considered regarding the flood damage assessment in the practical projects. The most of downstream areas close to the river in the case study were urbanized area that means reducing inundation area in the flood condition is the most important task in the flood management. In other words, we considered a direct and linear relationship between the inundation area and flood damage in this study. We applied HEC-RAS 2D model to simulate floods. We focused on the peak points of the floods in this study. Peak points of the different flood hydrograph with different annual exceedance probability (AEP%) were applied to develop relationship between rate of flow and inundation area. It should be noted that we developed optimization model for the long-term period in the monthly scale. Hence, it is necessary to approximate flood inundation area in the average monthly flow. The developed inundation area function is for flood events. Thus, the developed inundation area function is not directly useable for the optimization system. We converted this function to monthly inundation area function in which inundated area in different average monthly flow could be assessed.

Figure 8-4-1 displays flowchart of development of inundation area function in this research work. A regression model was applied to convert the peak point of flood events to the monthly flow. In other words, this regression model computes equivalent monthly flow of the flood peak point based on the recorded data in the study area. Hence, possible average flood inundation area in the monthly flow could be assessed. More details regarding development of inundation area function for monthly flow in the case study are available in the results and discussion.

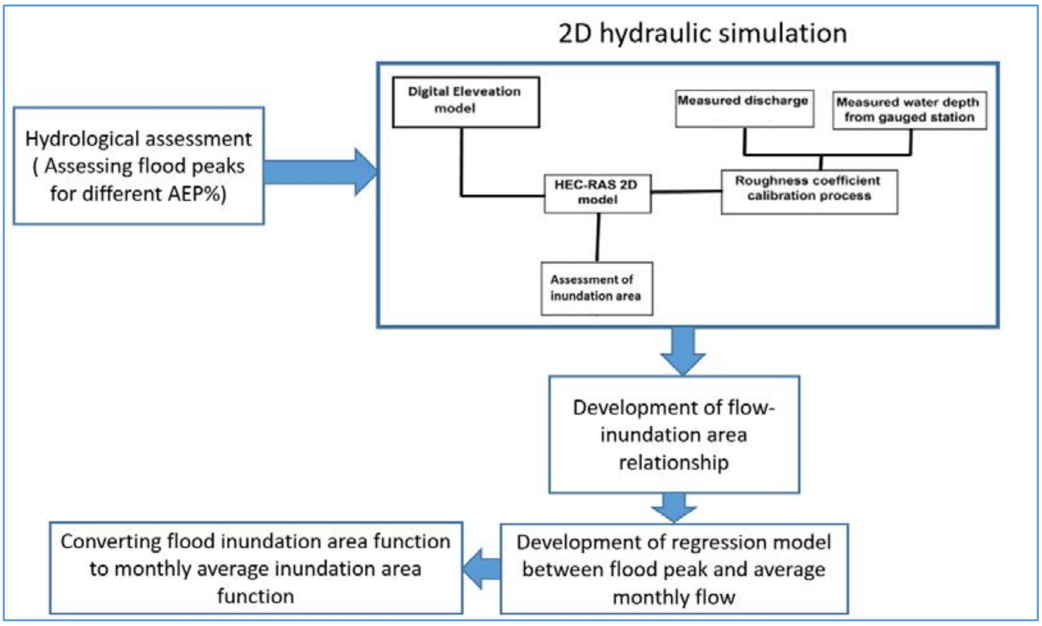



**Figure 8-4-1- Methodology of developing flow-inundation area relationship**

### 8.4.3 Environmental flow assessment method

Different methods could be used to assess environmental flow regime. We developed an appropriate method in accordance with the needs of the optimization model. Tennant proposed different ecological statuses in the assessment of the environmental flow that is applicable in all the environmental flow studies (Tennant, 1976). In fact, Environmental flow should be assessed considering the natural flow regime of the target river. Five different ecological statuses have been proposed including outstanding, excellent, good, fair and poor. As a description on these statuses, poor or minimum ecological status means that environmental flow should not be less than instream flow need in this status in all time steps. Outstanding ecological status means the environmental flow is able to provide a sustainable river ecosystem that might be appropriate for all of the aquatic species. Other statuses such as excellent and good provide habitat suitability less than outstanding status. We used this approach in the proposed framework. In this study, two environmental flow values were assessed in each time step including minimum environmental flow and outstanding environmental flow. Minimum environmental flow provides the poor ecological status in the river that is needed for all of the time steps. Moreover, outstanding ecological status is expected due to outstanding environmental flow in the river. Minimum environmental flow was assessed based on the minimum recommendation by the Tennant that is 10% of mean annual flow (MAF). Our initial assessment in the case study demonstrated that minimum environmental flow should not be less than this value in all of the time steps. Moreover, displayed flowchart in the figure 8-4-2 was used to assess outstanding environmental flow in the simulated period. It should be noted that time step in the optimization model is in monthly scale. Hence, environmental flow regime assessment was carried out in the monthly scale in this research work. Environmental flow could be implemented based on a constant minimum environmental flow or natural flow basis independent from months or monthly flow. We selected managing environmental flow based on the monthly flow because it is consistent with the management of the reservoir. Many previous studies demonstrated that monthly time step in the operation model is the best strategy for long-term management of the reservoirs (e.g Ehteram et.al, 2018b). Hence, monthly management of environmental flow is the best option for developing an integrated reservoir operation model. More clarification regarding the proposed framework for assessing environmental flow is needed. We applied a method to assess the outstanding environmental flow in which comparing mean monthly flow (MMF) and MAF is utilized to finalize the environmental flow regime. This method has originally been developed to improve the ecological status of the rivers (Tessmann, 1980). In other words, ecological status of the river in each month could strongly be dependent on the MMF. Hence, a systematic method for comparing MMF and MAF to finalize the environmental flow is recommended that is able to reduce the difference between natural flow and environmental flow.

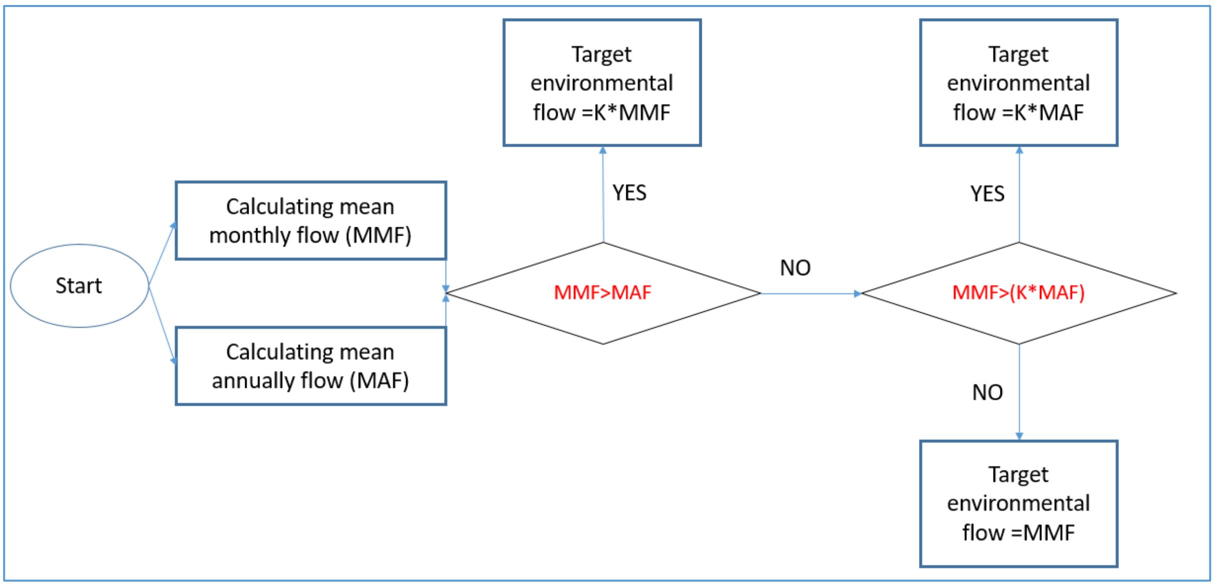



**Figure 8-4-2- Workflow of assessing outstanding environmental flow regime (target) in each monthly time step (K selected as 0.6 in this research work based on the expert opinions by city councils' environmental engineers)**

### 8.4.4 Reservoir operation optimization and measurement indices

Objective function is the main component in each optimization model that should be defined based on the initial purposes in the reservoir management. Equation 1 displays the objective function of the proposed framework where $TE_t$ is target of environmental flow regime. $RE_t$ is optimal release for environment, $TD_t$ is maximum water demand or target of water supply. $RD_t$ is optimal release for water supply and $NIA_t$ is normalized inundation area by the natural flow and $OIA_t$ is normalized inundation area in the optimal release for flood control. T is time horizon. Normalized inundation area was calculated by developed inundation area function in the section 2-2.

$$minimize(OF) = \sum_{t=1}^{T}(\frac{TE_t-RE_t}{TE_t})^2 + (\frac{TD_t-RD_t}{TD_t})^2 + (1/(\frac{NIA_t-OIA_t}{OIA_t})^2) \quad (1)$$

Three terms are recognizable in this equation including flood damage term, environmental flow term and water supply term. Flood damage term tries to maximize the difference between flood inundation area in the natural flow and in the optimal release from the reservoir. Environmental flow term minimizes the difference between target (outstanding environmental flow) and optimal release to the downstream. Furthermore, water supply term minimizes the difference between water demand and release for water supply in the simulated period.

Each reservoir operation model needs some constraints in accordance with the purposes of the optimization process. In the proposed framework the following constraints should be considered

1-Release for water supply should not be more than maximum water demand in the model

2-Storage in the reservoir should not be less than minimum operational storage of the reservoir

3- Storage in the reservoir should not be more than capacity of the reservoir

4- Environmental flow in each time step should not be less than minimum environmental flow

Different methods are applicable to add the constraints in the optimization model. Penalty function method is able to convert a constrained optimization problem to unconstrained optimization problem that is a good option for using evolutionary algorithms in the optimization process. Thus, we added four penalty functions to the optimization model as displayed in the equation 2. $ME_t$ is minimum environmental flow regime. $S_{max}$ and $S_{min}$ are maximum storage and minimum storage in the reservoir. C1 to C4 are constant coefficients that were determined based on the initial sensitivity analysis. In the equation 2, $S_t$ is storage in time step t and P1 to P4 are penalty functions.

$$\begin{cases} if S_t > S_{max} \rightarrow P1 = c1(\frac{S_t - S_{max}}{S_{max}})^2 \\ if S_t < S_{min} \rightarrow P2 = c2\left(\frac{S_{min} - S_t}{S_{min}}\right)^2 \\ if\ RE_t < ME_t \rightarrow P3 = c3\left(\frac{ME_t - TE_t}{TE_t}\right)^2 \\ if RD_t > TD_t \rightarrow P4 = c4(\frac{RD_t - TD_t}{TD_t})^2 \end{cases} \quad (2)$$

Each optimization system needs some indices to measure performance of the model. These indices measure robustness of the optimization system. According to the requirements in the case study, we selected some indices to measure performance of the system. Reliability index was utilized to analyze total supply of water demand and environmental flow in the simulated period as displayed in the equations 3 and 4. Moreover, root mean square error (RMSE) was applied to assess mean error in the supply of environmental flow regime due to importance of environmental flow supply in each month (equation 5). RMSE was utilized to measure performance of the optimization system in terms of storage loss as well (equation 6). Furthermore, two indices were added to measure performance of the system in terms of flood mitigation including $IR_{av}$ and $IR_{max}$. $IR_{av}$ is ratio of average normalized inundation area in the optimal release to average normalized inundation area in the natural flow. $IR_{max}$ is ratio of maximum normalized inundation area in the optimal release to maximum normalized inundation area in the natural flow.

$$RI_{water\ demand} = \frac{\sum_{t=1}^{T} RD_t}{\sum_{t=1}^{T} TD_t} \quad (3)$$

$$RI_{environmental\ flow} = \frac{\sum_{t=1}^{T} RE_t}{\sum_{t=1}^{T} TE_t} \quad (4)$$

$$RMSE_{environemntal\ flow} = \sqrt{\frac{\sum_{t=1}^{T} (RE_t - TE_t)^2}{T}} \quad (5)$$

$$RMSE_{Storage} = \sqrt{\frac{\sum_{t=1}^{T} (S_t - S_{Optimum})^2}{T}} \quad (6)$$

### 8.4.5 Evolutionary optimization

We applied different evolutionary algorithms to optimize reservoir operation as listed in the following table. More details are available in chapter 3

**Table 8-4-1- Short description of evolutionary algorithms**

| Name of algorithm | Short description | Reference |
|---|---|---|
| **Particle swarm optimization (PSO)** | stylized representation of the movement of organisms in a bird flock or fish school | (Kennedy and Eberhart, 1995) |
| **Genetic algorithm (GA)** | inspired by the process of natural selection by relying on biologically inspired operators such as mutation, crossover and selection | (Whitley, 1994) |
| **Differential evolution (DE)** | A known non-animal inspired algorithm that uses for multidimensional real-valued functions | (Qin et.al, 2008) |
| **Biogeography based optimization (BBO)** | motivated by biogeography that is the study of the distribution of biological species through time and space | (Simon,2008) |
| **Bat algorithm (BA)** | An animal inspired algorithm based on the social behaviour of the bats | (Yang and Gandomi, 2012) |

### 8.4.6 Decision-making system

As discussed earlier in this chapter, FTOPSIS was applied to select the best algorithm.

### 8.4.7 Case study

We applied the proposed framework in the Ross river dam in Townsville, Australia. Ross river is one of the important rivers in this area that is located in the tropical region. Townsville has a tropical climate. However, rainfall is not as high as other tropical areas due to geographical location. Winter months are dominated by blue skies and warm days that means rainfall is not considerable in these months. In contrast, the summer months are hot and humid starting in late October or November. Bursts of monsoon rains from late December until early April are expected. The dam has been constructed on the Ross

River as one of the important rivers in Queensland. The average annual rainfall in this catchment is 1143mm. Total annual inflow of the reservoir is 1600 to 1800 MCM. According to previous experienced floods, January to April is the most important flood season in this area. Supply of water for urban areas at downstream and flood control are the main responsibilities for the reservoir. Moreover, many valuable aquatic species lives at the downstream river that means environmental flow is one of the requirements in this river. Figure 8-4-3 displays location of the Ross River basin and the Ross River reservoir. Furthermore, figure 8-4-4 displays reservoir inflow in the simulated period and evaporation from the surface of the reservoir. Two sources were applied in the data collection including available data in the data bank of water monitoring information portal (WMIP of Queensland government) and reports by the Townsville city council. Table 8-4-2 displays more details regarding the catchment, reservoir, and current condition of operation.

**Table 8-4-2-More details regarding the river basin and dam**

| **Capacity (Mega litres)** | **250000 (Approximate)** |
|---|---|
| **Length of earth rock embankment (Km)** | 8.67 |
| **Height (m)** | 34 |
| **Type of spillway** | Controlled gated spillway |
| **Catchment area ($Km^2$)** | 750 |
| **Purpose of reservoir** | Water supply and flood control |
| **Maximum water demand** | In the current condition, a fixed value (5.17 $m^3/s$) could be defined based on the demands in the river basin |
| **Environmental flow requirements in the current condition** | Environmental flow is not defined in the structure of reservoir operation. The excessive flow is released to the downstream that might |

| | |
|---|---|
| | not be enough for aquatic environment |

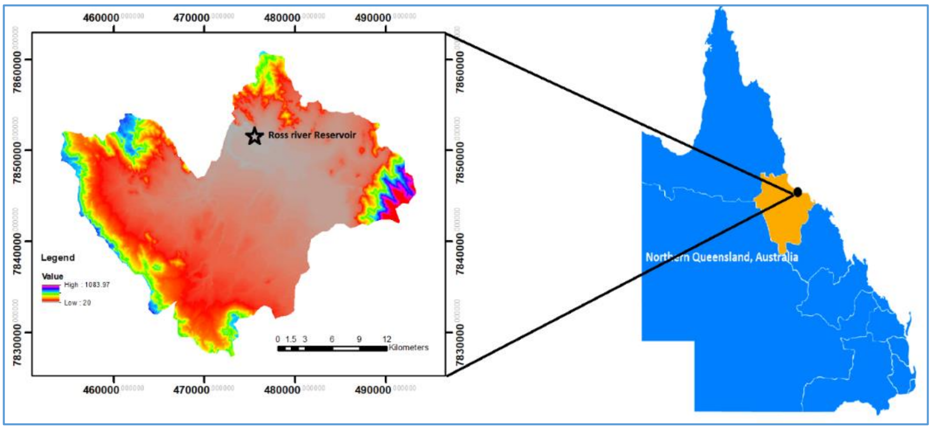



**Figure 8-4-3- Location of Ross River reservoir and its catchment**

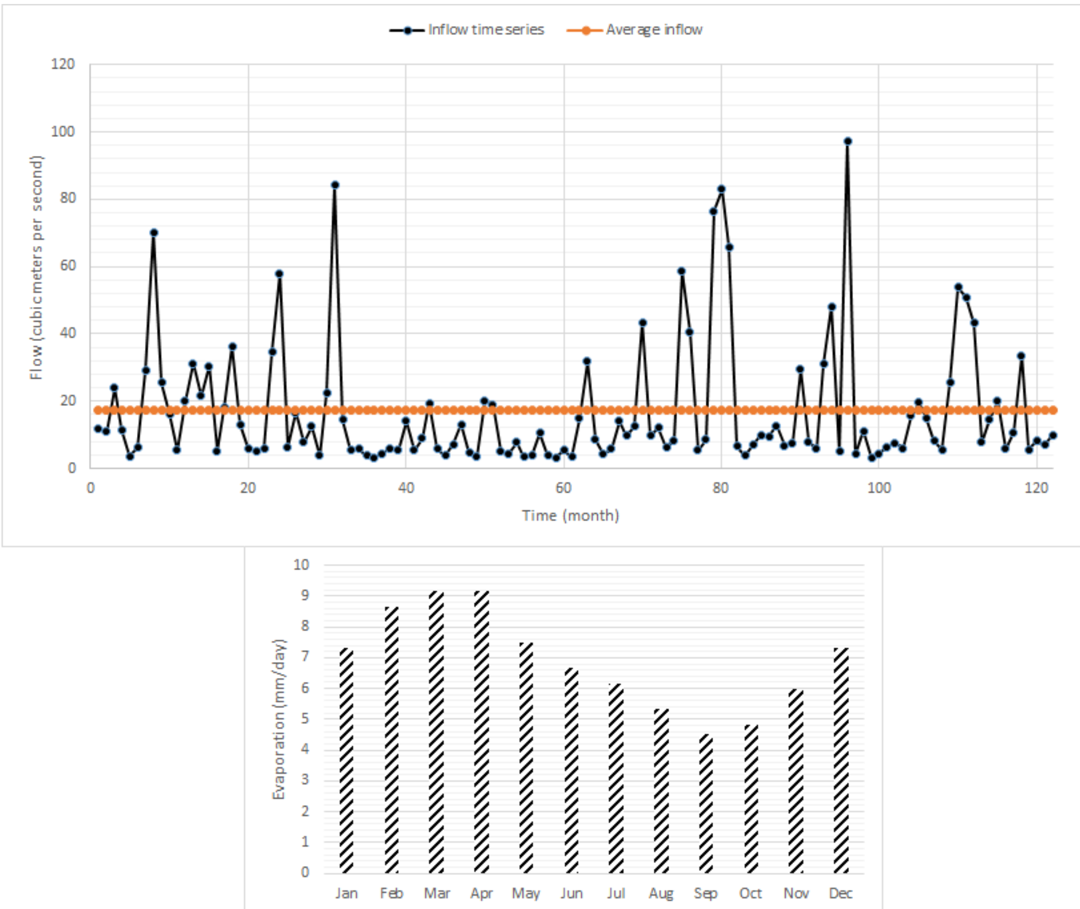



**Figure 8-4-4- Reservoir inflow in the simulated period and evaporation from the reservoir**

### 8.4.8 Results and Discussion

***Results of flood modelling**

In the first step, it is required to present result of the flood modelling in the case study. Figure 8-4-5 displays result of the inundation area simulation in eight cases of floods with different return periods . Inundation area is simulated by HEC-RAS 2D that is displayed in the Google Earth environment. Seemingly, the area of the inundation area has been increased in the major floods such as return period of 1000 years drastically that is logical. However, the difference between some floods such as 10 years and 20 years is not significant. Then, a regression model between peak of floods and average monthly flow was developed as displayed in the figure 8-4-6. Based on this regression model, normalized inundation area relationship for the optimization model was developed that is displayed in the figure 8-4-6 as well. It should be noted that we considered a wide range of flow rate in the simulated period in development of the normalized inundation area relationship. This relationship was one of the main inputs in the optimization model. Moreover, minimum environmental flow regime and outstanding environmental flow regime were other inputs in the optimization model that were used as minimum and target for environmental regime respectively.

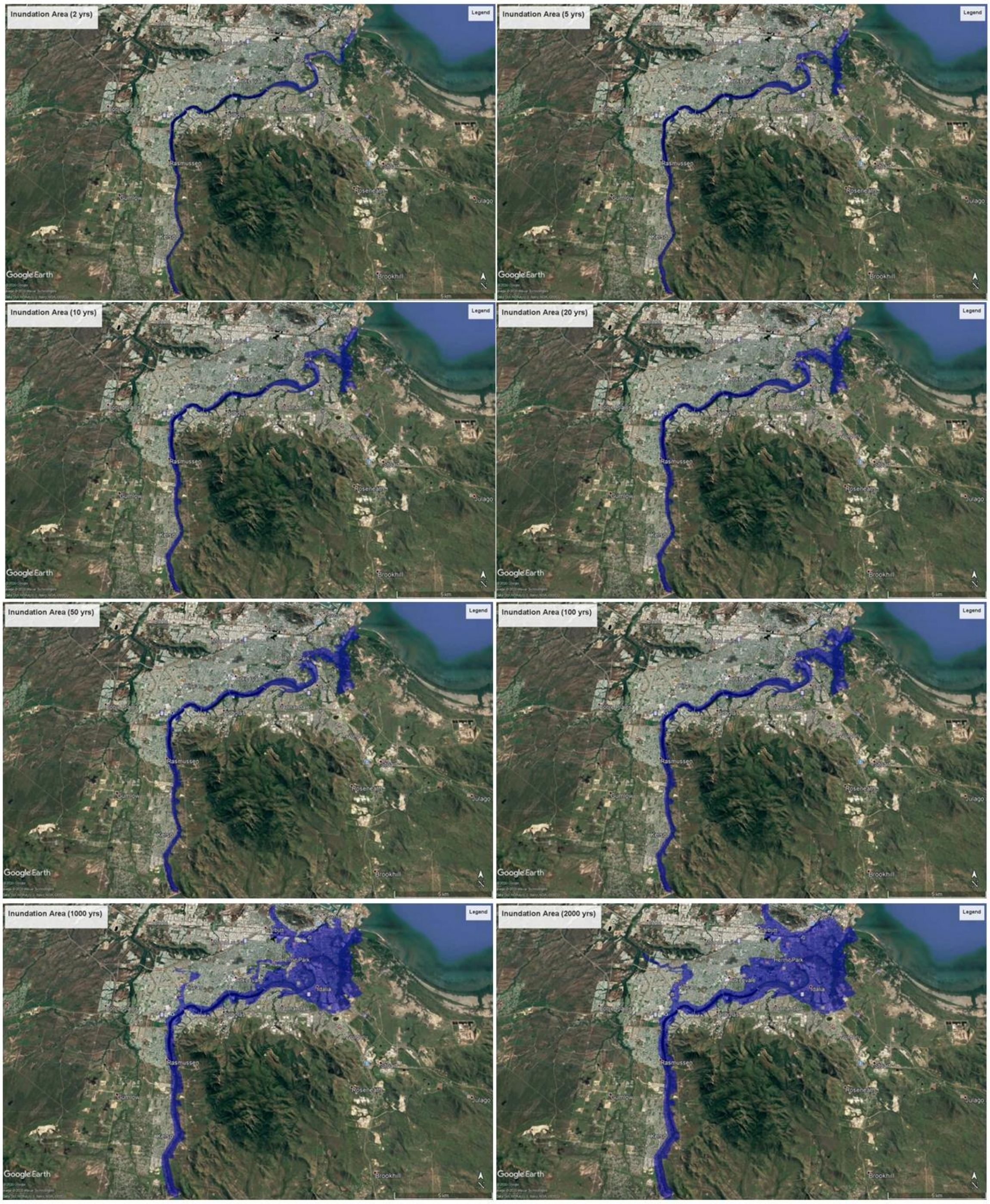



**Figure 8-4-5- Simulated inundation area in the peak point of different floods**

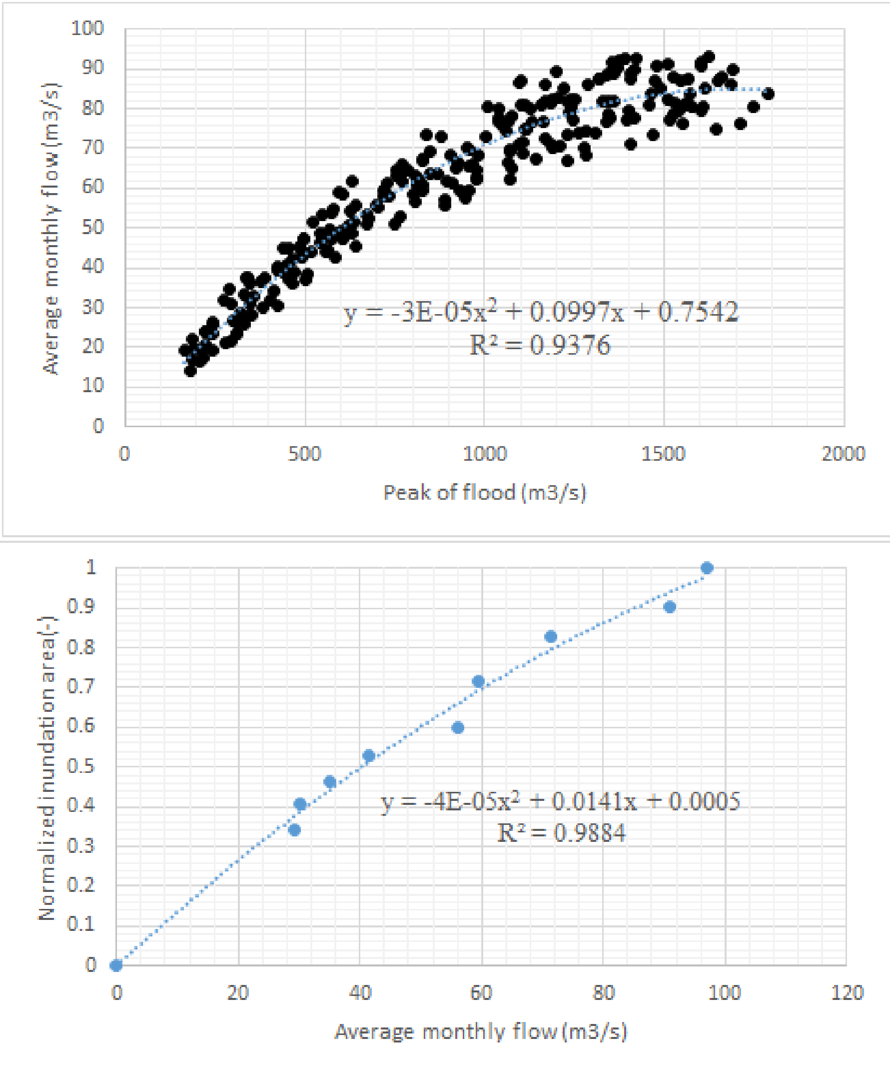



**Figure 8-4-6- Regression model for assessment of normalized inundation area in the optimization model**

***Results of optimization**

In the next step, it is necessary to present the outputs of the reservoir operation optimization. Four main outputs should be considered in this regard including environmental flow regime, release for water demand, storage in the reservoir and optimal flood damage. A point should be noted regarding the outputs of the optimization model. We did not consider overflow of the reservoir as the environmental flow regime because our model had an environmental flow component that should be able to mitigate environmental impacts. Overflow is helpful in the wet months. However, we did not consider it as the environmental flow to increase reliability of the environmental flow supply. Figure 8-4-7 displays release for environment or proposed environmental flow by different algorithms. Some points should be noted in this regard. First, the performance of algorithms is different that means using measurement indices is essential and it is not possible to judge on the results only based on the observation. Secondly, the performance of the minimum environmental flow penalty function seems perfect in most of the algorithms. However, BBO is not perfect in this regard. The proposed flow regime by this algorithm is less than minimum environmental flow regime in some time steps. No upper limit was considered for the environmental flow that might be advantageous. The initial assumption in the environmental flow assessment was defined as the higher flow which is able to provide higher suitability in the river ecosystem. In fact, we allowed optimization model to increase environmental flow more than defined target. Thus, the proposed environmental flow by different algorithms is more than target of the environmental flow in the optimization model in some months.

Figure 8-4-8 displays supplied water demand by different algorithms. We defined a constant value equal to 5.17 m3/s as the water demand in each time step. This value was defined based on the recommendations by the Townsville city council. The performance of the maximum demand penalty function is not acceptable for some algorithms such as PSO and BBO. The supplied demand is more than maximum defined water demand in some time steps for these algorithms. However, they supply part of water demand in other time steps. It seems that the performance of the GA is different compared with other algorithms. It is sustainably able to supply water demand that could be an advantage for applying this classic algorithm. The performance of the other algorithms is not sustainable regarding water supply. At the first glance, it shows the distinction of the genetic algorithm. However, water supply is only one of the components in a sustainable reservoir operation. Thus, it is essential to consider all of the responsibilities of the reservoir for judging on the performance of the optimization system.

Storage in the reservoir is another output of the optimization model that should be presented. Figure 8-4-9 displays storage time series in the reservoir for the simulated period. As presented, two penalty functions were added to the system regarding storage including minimum operational storage and capacity of the reservoir. Time series of the minimum storage and capacity are displayed in the figure 8-4-10 as well. The performance of the penalty functions is important in the evaluation of the optimization system. It seems that the performance of maximum storage function is perfect for all of the algorithms. The maximum storage in the reservoir for all algorithms is equal to the available capacity of the reservoir. However, the performance of the minimum storage function is not perfect as like as the maximum storage function due to lack of sufficient reservoir inflow in some time steps. It seems that PSO is the weakest algorithm in this regard. The storage in the reservoir by this algorithm is less than minimum operational storage in some months. Moreover, GA is not perfect as well. However, the performance of all algorithms is generally defensible regarding the storage in the case study. Another responsibility for the reservoir is flood control. Thus, it is necessary to assess normalized inundation area optimized by the reservoir as a tool for flood control. Figure 8-4-11 displays normalized inundation area by optimal release of different algorithms and in the natural flow. It seems that the flood hazard in the simulated period is serious. Inundation area in some months is close to one that means major floods in these months is probable. The results by different algorithms demonstrate significant role of the reservoir to reduce possible flood damage in a Australian tropical region. However, the performance of algorithms are not similar in terms of reducing inundation area in different time steps. Performance of some algorithms such as PSO is not robust. It seems that it is not able to reduce normalized inundation area in some time steps. However, judgment on the performance of the algorithms is not possible by the observation of inundation area time series in the simulated period that means using measurement indices will be helpful to discuss on the results of the algorithms.

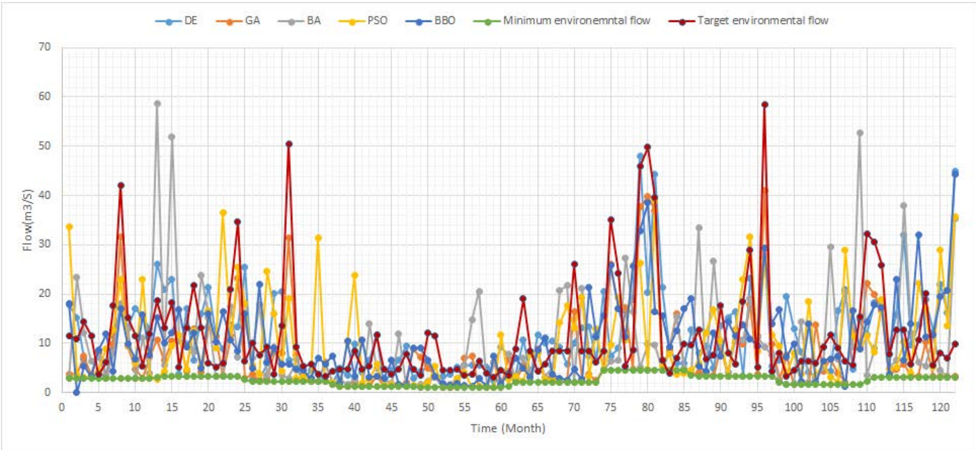



**Figure 8-4-7- Proposed environmental flow regime by different algorithms**

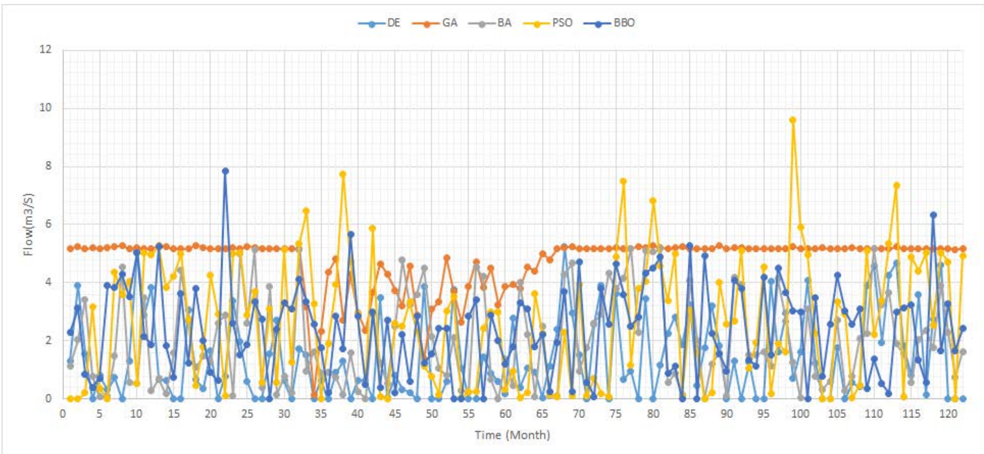



**Figure 8-4-8- Water supply by different algorithms**


**Figure 8-4-9- Storage time series in the reservoir by different algorithms**

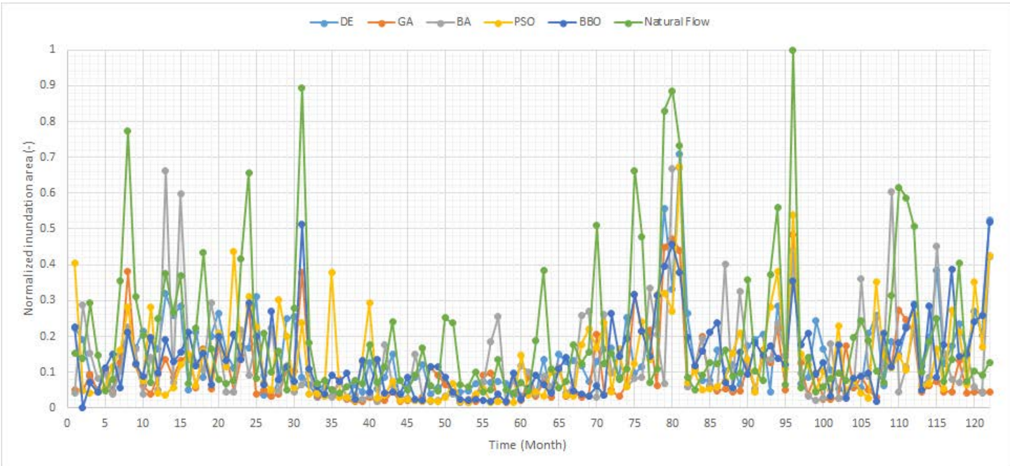



**Figure 8-4-10- Normalized inundation area by different algorithms**

***Performance analysis and discussion**

Figure 8-4-11 displays computed measurement indices based on the outputs of the optimization model. Reliability index for water supply indicates that the performance of GA in terms of water supply is outstanding compared with other algorithms that should be considered as the significant advantage for using this evolutionary algorithm in the optimization process of the proposed framework. Conversely, the performance of DE is very weak that means it is not a proper algorithm to supply water by the proposed framework. The performance of other algorithms is better than DE. However, they are not robust as much as GA to supply water demand. RMSE of storage is another index that demonstrates the robustness of the optimization system. It seems that performance of different algorithms in terms of maintaining optimal storage in the reservoir is similar. However, the weaker performance of PSO is clear. In other words, this algorithm is not able to maintain mean optimal storage level in the reservoir as appropriate as other algorithm such as GA or DE.

Reducing inundation area is another output of the optimization model. As presented in the section 2-5, two indices were considered to measure performance of the system in terms of mitigating flood damage including IRav and IRmax. These indices indicate ratio of average inundation area by the optimization system to average inundation area in the natural flow and ratio of maximum inundation area by the optimization system to maximum inundation area in the natural flow. These indices will be helpful to measure performance of the system in terms of flood damage mitigation. Based on the outputs, the performance of GA is more robust than other algorithms in terms of reducing inundation area in both indices. The weak performance of either PSO or DE or BA in terms of reducing inundation area should be considered in the final assessment of the optimization system. Another responsibility for the reservoirs in the Australian tropical regions is supply of environmental flow. If a reservoir operation model could not supply environmental flow similar to the main responsibilities such as water supply and flood control it is not robust optimization model. The importance of environmental impacts of the reservoir should be considered like the main responsibilities of the reservoir. Supply of environmental flow is one of the most effective solutions to mitigate environmental impacts at downstream of the reservoir. Hence, we applied two indices for measuring the performance of the optimization system in terms of supply of environmental flow including reliability index for environmental flow and RMSE for environmental flow. The first index demonstrates how the optimization system is able to supply total environmental flow in the simulated period compared with target of total environmental flow. Furthermore, RMSE indicates mean error for supplying environmental flow in the simulated period. Lower RMSE is favorite. It demonstrates sustainability in the supply of environmental flow. The weak performance of GA in terms of total environmental flow supply is clear compared with other algorithms. Interestingly, when an algorithm is able to supply more water demand, it is not able to supply sufficient environmental flow at downstream that seems logic. We face low inflows in some months in the Australian tropical region that means appropriate simultaneous supply of environmental flow and water demand is not possible due to low inflow and constraints of the storage in the reservoir. In contrast, the robust performance of DE indicates that this algorithm is more reliable in the supply of total environmental flow. However, RMSE of the environmental flow indicates another story by different algorithms. GA is the best algorithm in terms of RMSE. It is able to provide the lowest mean error compared with other algorithms that might be an advantage to keep sustainable ecological status at downstream river.

Results of computing measurement indices show contradictory outputs that makes it impossible to make decision for selecting the best algorithm based on the observation of the original results. It should be noted that outputs by algorithms demonstrate necessities of utilizing several algorithms in the optimization system due to different performance of algorithms in terms of water supply, environmental flow supply and flood control by the reservoir. A significant difference between outputs indicates that there is no guarantee to get the global optimization by the evolutionary algorithms in the optimization systems of the reservoir. In fact, the objective function of the reservoir operation is complex that might not be solved properly by an algorithm. Thus, it is necessary to apply several algorithms to reduce uncertainties in the assessment of the global optimization in the reservoir operation models. It should be noted that the purpose of this research work is a novel framework for global optimization of the reservoir operation. It could be applied in all the reservoirs where are responsible for water supply and flood control. The results of the case study demonstrated that this framework is applicable in the Australian tropical regions.

We utilized FTOPSIS method as the decision-making system in this research work. Determining the weight of importance and rating of the alternatives are the main requirements for using this method. Seven classes were considered in the assessment of the weight of the importance including very low, Low, medium low, medium, medium high and very high. Reliability index of water supply was considered as the medium high. However, the importance of environmental sustainability is more than water supply. Thus, it should not be considered as the high or very high in the system. Moreover, supply of water in the case study is possible by other water resources as an alternative. The importance of storage in the reservoir is not considerable. Thus, medium weight of importance seems sufficient for this index. Flood management is a key responsibility for the reservoir in the Australian tropical regions. In fact, there are serious concerns regarding direct and indirect damage of floods in these regions in the wet months. For example, many major floods have been experienced in the previous years that caused significant damage to the urban areas at downstream of the Ross river dam. Thus, the weight of importance for the inundation area indices is sensitive. It should be noted that flood control is the main responsibility of the dam in Townsville that is not possible by other alternatives. In fact, supply of water could be possible by other available water resources in the region. However, they increase cost of water conveyance for the city council. In contrast, using the Ross River dam is the only option to control flood damage at the downstream urban areas. We applied two indices regarding flood control by the reservoir operation in the developed framework that increase reliability of the system to mitigate flood damage. Importance of $IR_{av}$ and $IR_{max}$ were considered as the medium high and high in the decision-making system. Environmental flow supply is another aspect in the decision-making system that would be measured based on the two computed indices. Reliability index for environmental flow was considered as very high in the decision-making system. The importance of sustainable ecological status at downstream river is in high priority. Moreover, RSME of environmental flow was considered as medium. It should be noted that allocating the weight of importance in the FTOPSIS is dependent on the case study and technical considerations that is one of the significant advantages of using FTOPSIS as the decision-making system. In fact, FTOPSIS is able to take into account technical problems in the reservoir management that could affect the weight of importance. Due to this strength, we recommend utilizing the FTOPSIS in the future assessment of the optimization system in the water resources management and engineering. In the next step, it is essential to discuss on the rating of alternatives in the decision-making system. Table 8-4-3 displays the rating of alternatives in this research work. The difference between some algorithms is not considerable in some indices. Hence, rating of alternatives for some algorithms are the same for some measurement indices that is logical. The final output of the decision-making system could be observed in the figure 8-4-12. GA is the best method to optimize reservoir operation by the proposed framework that should be considered in the future studies. It seems that the performance of other algorithms is remarkably weaker than GA in the proposed framework. It is needed to compare the results of this research work with previous studies in term of selecting the best algorithm to optimize reservoir operation. A review on the literature demonstrates that a long list of evolutionary algorithms have been tested in the reservoir operation. Most of these studies claimed that the performance of new generation algorithm such as BA is better than classic and old algorithm such as GA. However, this research work does not corroborate their conclusion for using evolutionary algorithms. We do not claim that GA is best option for all of the reservoir operation frameworks. Undoubtedly, the performance of this algorithm is very different based on the developed objective function and even the feature of the case study might be effective on the results. We point out that judgment on the evolutionary algorithms is not possible easily and recommendations by previous studies for selecting the best algorithm to optimize reservoir operation are not reliable in all the cases. We recommend utilizing several algorithms in each case study. However, if a previous study with the exact similar objective function recommends using an algorithm, it is cautiously reliable. It is only fully reliable, if all details including inflow and other reservoir parameters will be the same. No algorithm would guarantee the global optimization in the reservoir operation problems due to complexities of the objective function. It should be noted that previous mathematical studies on the optimization algorithms such as evolutionary algorithms utilized simple benchmarking function. Thus, the performance of these algorithms must be tested in the complex functions such as the objective function of the reservoir operation.

It is needed to discuss on the results with a focus on the Australian tropical regions based on the selecting outputs of the GA as the best algorithm. It seems that flood and environmental flow management in these regions is a significant problem. Thus, right operation of the reservoir is such sensitive. Increasing the storage of the reservoir is one of the options to reduce uncertainties in the flood and environmental flow management in these regions. It should be noted that population of the tropical regions of Australia is not considerable in the current condition that means water demand is not remarkable. However, the projection of the population demonstrates that increasing population in the future is inevitable. Hence, supply of environmental flow is problematic due to low inflow in some months. In this situation, the role of reservoir in the supply of environmental flow will be considerable.

Moreover, it is essential to discuss on the application of the proposed framework. The proposed framework would be helpful to evaluate reservoir operation in the long-term period with focus on the past events. In fact, the proposed framework is a simulation of the reservoir operation. It is useable to forecast reservoir operation in the future period. Coupling of reservoir inflow models and the proposed model is recommendable in this regard. However, we recommend using the proposed model to forecast reservoir operation in the future period cautiously. Most of the streamflow forecasting models are not reliable. On the other hand, the proposed framework is applicable to assess impact of climate change on the flood management and environmental flow supply at downstream of the reservoir. The climate change models assess impacts on the rainfall in the future periods. Then, the runoff routing models simulate the reservoir inflow in the future long-term period. Utilizing the proposed framework is advantageous to project climate change impacts on the flood and environmental flow management at downstream of the reservoir.

Each system has some limitations and advantages that should be discussed. Furthermore, it should be discussed why the proposed mechanism is successful in all case studies. The main limitation of the proposed framework is verification of the 2D hydraulic model. It should be noted that calibration or verification of 2D model is an arduous task. In this research work, we applied the previous studies by the city council to verify the 2D model. However, it is not possible in many case studies. Field studies are helpful in this regard but it might be expensive. Measurement of depth and velocity in different points should be considered in the field studies. In contrast, low computational complexity is an advantage for the developed system. In the computer science, the term of computational complexity is defined as the given time and memory to the optimization algorithm to find the best solution. Numerous simulations and covering long-term periods are the requirements in the practical project, if computational complexity of the system is high. The proposed framework due to low computational complexity has sufficient flexibility for utilizing in the practical projects. The main reason for the success of the developed model is to consider a robust method to assess flood damage and a systematic method to assess environmental flow in the structure of the optimization system of the reservoir operation. Another advantage of the proposed framework is upgradability that means it is possible to add other advanced methods for environmental flow and flood damage assessment in the structure of the optimization system. We recommend utilizing the proposed framework in the future simulations of the reservoir operation. It is recommendable especially in areas in which sequence of dry months and wet months is problematic in the reservoir operation. In fact, the proposed framework would be helpful to assess the reservoir operation to get the lessons for the improvement of the reservoir operation. Simulation of the future period by coupling the proposed model and climate change model should be noted as an advantage of the developed method.

One of the important questions that should be responded is how selecting the GA as the best optimization method could be justified. In fact, GA is not robust in terms of environmental flow supply. However, it was selected as the best algorithms by the FTOPSIS method. It is related to the prioritizing the purposes in the management of the reservoir. Flood control is an important responsibility for the reservoir. The performance of GA is robust regarding the flood control in the study area. Moreover, GA is highly robust in terms of water supply due to high reliability index. Hence, GA could be the best method though it is not able to supply environmental flow properly as well other algorithms. The results of this research work corroborate that optimal management of the reservoir could be complex and selecting the best method should be based on all prioritized purposes.

It is necessary to compare this research work with the previous studies regarding the used approaches. In other words, it should be responded how the previous studies support the approaches of this research work. The previous studies corroborated that using a robust decision-making system is a serious need in the reservoir operation that would be able to consider all stakeholders' benefits (Ehteram et.al, 2018c). Many previous studies demonstrated that using FTOPSIS is advantageous for complex decision-making system due to possibility of applying expert opinions for reducing the conflict of interests (e.g., Ashtiani et.al, 2009; Wang and Elhag 2006; Ding, 2011). It is demonstrated that considering environmental flow should be prioritized in the decision-making system based on the needs and technical considerations. Furthermore, flood control by the reservoirs is challenging in the reservoir operation that means flood control should be prioritized for the regions in which flood is problematic (Huang et.al, 2018). We applied two dimensional hydraulic modelling for developing flood damage function which has been recommended in the literature (e.g., Chen et.al, 2017).

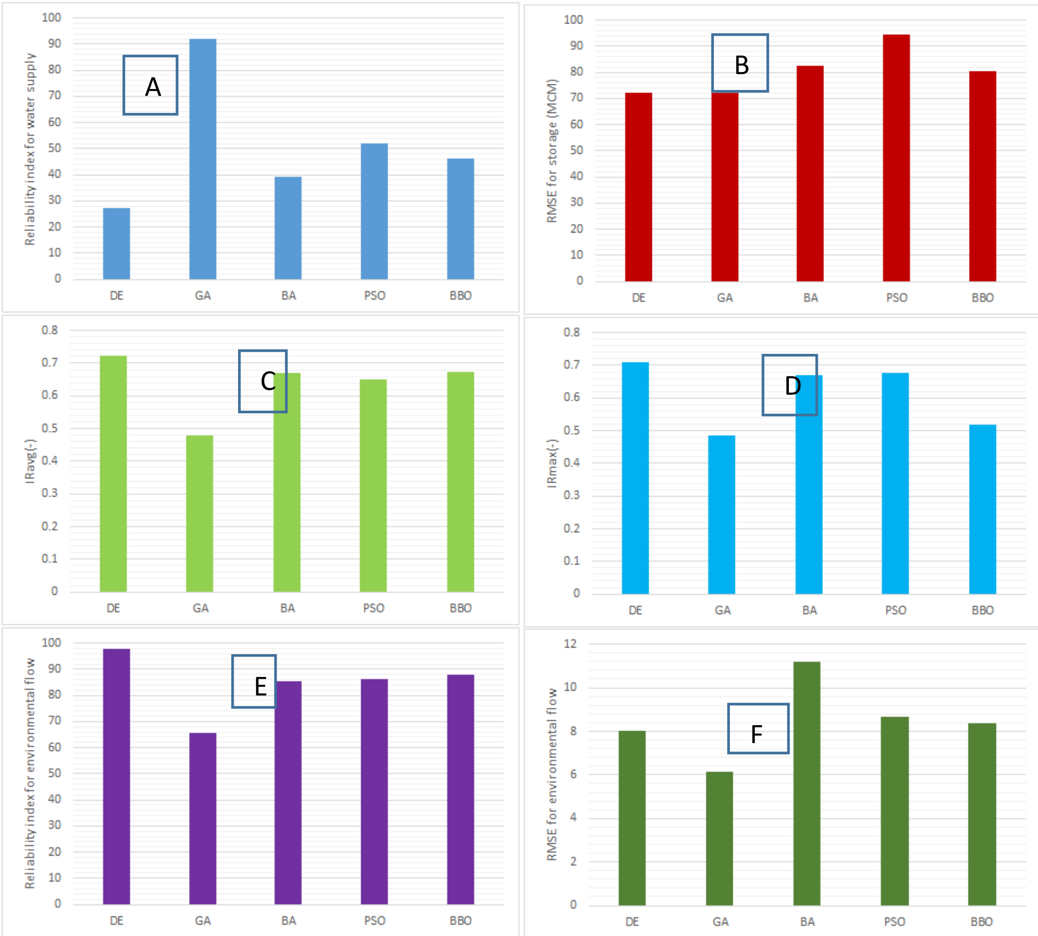



**Figure 8-4-11- Measurement indices of the optimization system (A: Reliability of water supply, B: Mean error of optimal storage in the reservoir, C: Average inundation area index, D: Maximum inundation area index, E: Reliability of environmental flow supply, F: Mean error of environmental flow supply)**

**Table 8-4-3- Rating of alternatives (VP, P, RP, RG, G, VG means very poor, poor, relatively poor, relatively good, good, and very good respectively)**

| Algorithms | RI (water supply) | Algorithms | RMSE (storage) |
|---|---|---|---|
| DE | VP | DE | G |
| GA | VG | GA | G |
| BA | RP | BA | G |
| PSO | F | PSO | VG |
| BBO | RP | BBO | G |
| Algorithms | IR(average) | Algorithms | IR(maximum) |
| DE | VG | DE | VG |
| GA | RP | GA | RP |
| BA | G | BA | G |

| | | | |
|---|---|---|---|
| PSO | G | PSO | G |
| BBO | G | BBO | F |
| Algorithms | RI (environmental flow supply) | Algorithms | RMSE (environmental flow supply) |
| DE | VG | DE | RG |
| GA | P | GA | G |
| BA | G | BA | P |
| PSO | G | PSO | RG |
| BBO | G | BBO | RG |

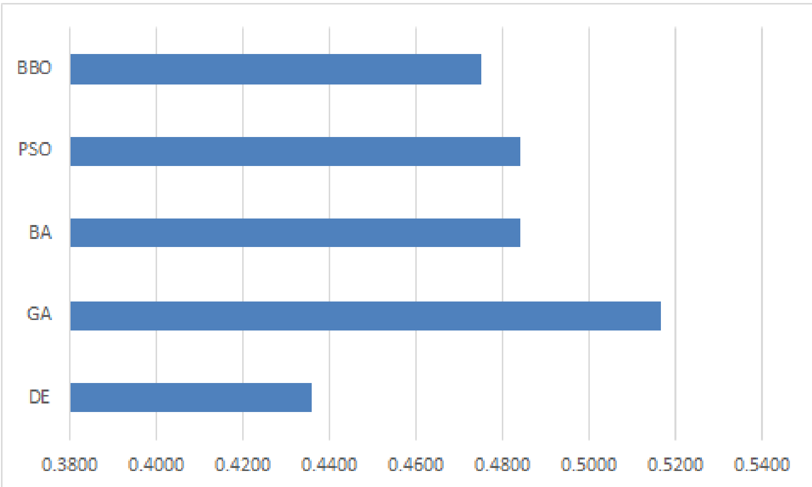



**Figure 8-4-12- Final ranking by the FTOPSIS method**

As a summary of this section, we developed a novel optimization system to simulate optimal operation of the reservoir in terms of flood damage and environmental flow management with a focus on the Australian tropical region where is a challenging area to manage flow at downstream. 2D hydraulic model was used to simulate inundation area function at downstream to develop a normalized inundation area function. Moreover, minimum environmental flow regime and target of environmental flow regime were assessed based on the historical flow data in the simulated period. Different evolutionary algorithms were applied to optimize reservoir operation. Based on the results, the performance of the optimization system is acceptable. However, it is not perfect. Due to limited storage area in the case study, right reservoir operation is a sensitive task to manage flood damage and environmental flow regime. Increasing storage of the reservoir is an option to improve the management of the flood and environmental flow. GA was the best algorithm to optimize reservoir operation that is able to optimize all of the defined tasks for the reservoir. However, its performance is not excellent in terms of environmental flow supply.

## ***<u>8.5 Using environmental flow models in multi-reservoir operation</u> (framework 5)***

### 8.5.1 Case study and problem definition

The proposed method was implemented in the Jarood River in Iran. Latian and Mamloo dams have been constructed on this river for supplying water demands. Due to high water demand, supply of environmental flow at downstream river habitats might be challenging. On the one hand, department of environment requests ideal environmental flow regime at downstream of the reservoirs. On the other hand, regional water authority has serious concerns regarding supply of water demand. Hence, using an integrated optimization model seems necessary. In other words, minimizing loss of the environmental flow and water supply and storage constraints were considered in the integrated optimization model. The proposed model is applicable for all the multireservoir cases. Figure 8-5-1 displays location of the Jajrood river basin and Latian and Mamloo reservoirs.

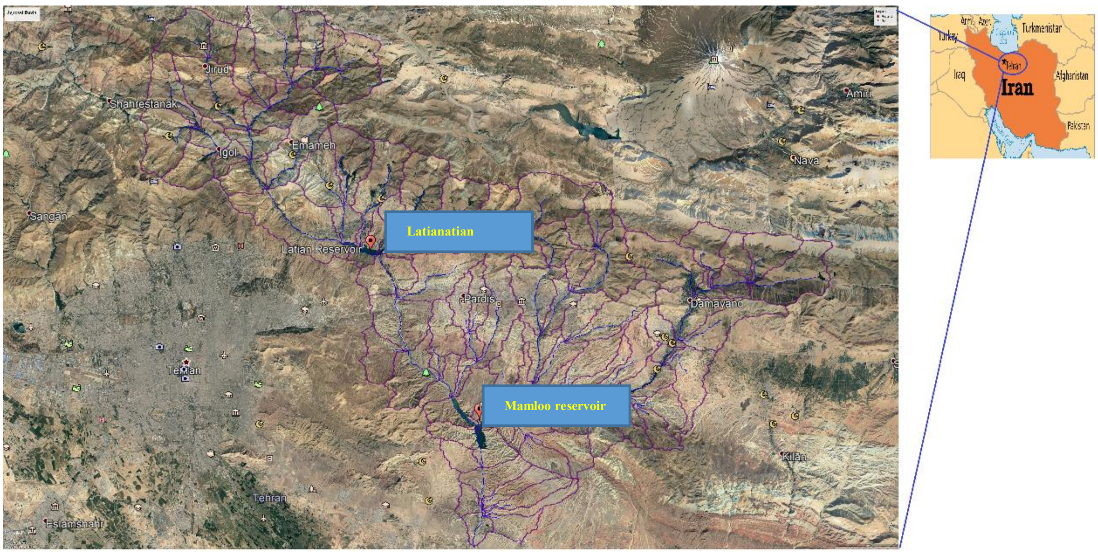



**Figure 8-5-1- Location of Latian and Mamloo reservoirs in a google earth view**

### 8.5.2 Forecasting inflow

Soil and water assessment tool (SWAT) was utilized to simulate inflow of the reservoirs. Moreover, we used SWAT-CUP as a standalone program to calibrate and validate outputs of the SWAT. More details are available in chapter 6. Digital elevation model, slope map, land use and soil map are the main inputs of the rainfall-runoff model. SWAT needs weather data including maximum and minimum temperature and rainfall in daily scale as well. A total 360 months period was considered as the simulated period for calibration and validation of the rainfall-runoff model and optimization of the reservoir operation. 300 months (first month to $300^{th}$ month) were selected as the calibration period of the rainfall-runoff model. Rest of the simulated period including 60 months was selected as the validation period of the rainfall-runoff model. Then, the first 50 months of the validation period were selected as the simulated period for the reservoir operation optimization. It should be noted that this research work was part of a bigger research work in the study area that included many other optimizations and simulations. Thus, simulated time of the reservoir operation optimization was reduced in the main research work to decrease running time of the optimization code. More details on the steps of the reservoir inflow simulation are presented as follows.

1-Selecting 300 months of recorded data as the calibration period and collecting required data including daily temperature and precipitation data.

2- Given the availability of the recorded monthly flow only in one of the inflow branches to the Latian dam, this tributary was selected as the target for calibrating model by SWAT-CUP. No hydraulic structure or water diversion project has been constructed at the upstream tributary in which flows were recorded. Thus, the recorded data could be used for calibration of the SWAT model in the Jajrood river basin.

3-Calibrating outputs of the SWAT model by SWAT-CUP and adoption of calibrated coefficients for other subbasins. Then, validating results in 60 months period as the validation period.

4- Generating inflow of the reservoirs for the simulated period.

Due to importance of the calibration and validation process in the rainfall-runoff model, it is essential to present the calibration methodology of the SWAT-CUP. This software is a tool for SWAT Calibration and Uncertainty analysis. One of the known algorithms to calibrate rainfall-runoff model in this program is Sequential Uncertainty Fitting (SUFI2) algorithm. SUFI-2 performs a combined optimization and uncertainty analysis using a global search procedure (More details by Abbaspour et.al, 2013). Many parameters might be effective in the runoff modelling. However, SWAT-CUP generally considers four calibration parameters including CN2.mgt (Initial SCS runoff curve number for moisture condition II), ALPHA_BF.gw(Alpha factor for groundwater recession curve of the deep aquifer(1/days)), GW_DELAY.gw (Ground water delay time) and GWQMN.gw (Threshold depth of water in the shallow aquifer required for return flow to occur (mm H2O)). SWAT-CUP tries to find the best values for the calibration parameters to minimize the difference between observed stream flow and simulated stream flow. Furthermore, it is required to measure the performance of the runoff model. Hence, The Nash–

Sutcliffe model efficiency coefficient (NSE) was used as the measurement index (Gupta and Kling, 2011). Equation 1 displays mathematical form of this index (Abbaspour et.al, 2015).

$$NSE = 1 - \frac{\sum_{t=1}^{T}(M_t - O_t)^2}{\sum_{t=1}^{T}(O_t - O_m)^2} \tag{1}$$

where $M_t$ is forecasted inflow by model in each time step, $O_t$ is observed or recorded inflow in each time step and $O_m$ is mean observed or recorded inflows in the simulated period. It should be noted that this index is one of the known indices for estimating robustness of the hydrologic models.

### 8.5.3 Optimization model

Main component of each optimization model is objective function. Equation 2 displays developed objective function for this research work where T is time horizon, $D_{i,t}$ is maximum water demand of i-th reservoir in month t, $R_{i,t}$ is release for water demand of i-th reservoir in month t, $E(\text{target})_{i,t}$ is ideal environmental flow of i-th reservoir in month t and $E_{i,t}$ is release for environmental flow of i-th reservoir in month t. Other parameters are penalty functions that will be discussed.

$$Minimize(OF) = \sum_{t=1}^{T}\sum_{i=1}^{2}\left(\frac{D_{i,t}-R_{i,t}}{D_{i,t}}\right)^2 + \left(\frac{E(\text{target})_{i,t}-E_{i,t}}{E(\text{target})_{i,t}}\right)^2 + PE1_{i,t} + PE2_{i,t} + PS1_{i,t} + PS2_{i,t} + PD_{i,t} \tag{2}$$

The variables in the optimization model are release for water demand ($R_{i,t}$) and release for environmental flow ($E_{i,t}$). In fact, the optimization model tries to find the optimal sequence of releases for water supply and environmental flow from each reservoir. Storage might be changed in each time step of the simulated period. Hence, it is updated in each time step. Some constraints should be considered for the reservoir operation including constraints on the storage, supply of water demand and supply of environmental flow regime. More details are described.

1-Storage must be less than the capacity of the reservoir. Moreover, storage must be more than the minimum operational storage of the reservoir.

2- Maximum release for the water demand in each time step must not be more than the defined water demand

3-Two environmental flow regimes were defined including minimum and ideal environmental flow regimes. Ideal environmental flow regime is the target of the optimization model. Thus, release for environmental flow should not be more than ideal environmental flow. Conversely, Environmental flow should not be less than minimum environmental flow in each time step. More details regarding the environmental flow regimes will be presented.

Converting constrained optimization problem to unconstrained optimization problem is one of the applicable solutions to insert the constraints in the structure of the optimization model. The penalty function method is a known method in this regard that has broadly been utilized in the previous studies. Hence, this method was used in this research work. In other words, the penalty functions increase the reservoir operation penalties to find the best responses. Two penalty functions were added for minimum and maximum storage constraints as displayed in the following equation.

$$\begin{cases} if S_{i,t} > S_{\max(i,t)} \rightarrow PS1_{i,t} = c1(\frac{S_{i,t}-S_{\max(i,t)}}{S_{\max(i)}})^2 \\ if S_{i,t} < S_{\min(i,t)} \rightarrow PS2_{i,t} = c2(\frac{S_{\min(i,t)}-S_{i,t}}{S_{\min(i,t)}})^2 \end{cases} \quad (3)$$

Two penalty functions were added for minimum and ideal environmental flow regime that are displayed in the equation 4.

$$\begin{cases} if E_{i,t} > E_{target(i,t)} \rightarrow PE1_{i,t} = c4(\frac{E_{i,t}-E(\text{target})_{i,t}}{E(\text{target})_{i,t}})^2 \\ if E_{i,t} < E_{\min(i,t)} \rightarrow PE2_{i,t} = c5(\frac{E(\min)_{i,t}-E_{i,t}}{E(\min)_{i,t}})^2 \end{cases} \quad (4)$$

One penalty function was added regarding the water demand as displayed in the equation 5

$$if\ R_{i,t} > D_{i,t} \rightarrow PD_{i,t} = c3(\frac{R_{i,t}-D_{i,t}}{D_{i,t}})^2 \quad (5)$$

It should be noted that the constant coefficient in the penalty functions (c1 to c5) could be determined by the sensitivity analysis. Furthermore, storage of the reservoirs is changed in each time step. Hence, Equation 6 was used to update the storage of each reservoir.

$$S_{t+1} = S_t + I_t - R_t - E_t - F_t - \left(\frac{V_t * A_t}{1000}\right)\ , t = 1,2,\ldots,T \quad (6)$$

where $S_t$ is the storage at time period t, $I_t$ is the reservoir inflow at time t, $V_t$ is the evaporation rate (evaporation flow per surface unit) at time t. $A_t$ is the area of reservoir surface at time t, $R_t$ is the release for water demand at time t, $E_t$ is the release for environmental flow at time t and $F_t$ is the overflow in time period t. T is the time horizon. Overflow ($F_t$) in each reservoir was defined based on the equation 7. The overflow was not considered as the environmental flow regime in the optimization framework. It might be the instream flow of the downstream river. However, controlled regime to the downstream was considered as the environmental flow for increasing the reliability of the environmental flow supply. It should be noted that release for water supply ($R_t$) is directly being pumped from each reservoir.

$$\begin{cases} if\left(S_t + I_t - \left(\frac{V_t \times A_t}{1000}\right)\right) \geq S_{max} \rightarrow F_t = S_t + I_t - \left(\frac{V_t \times A_t}{1000}\right) - S_{max} \\ if\left(S_t + I_t - \left(\frac{V_t \times A_t}{1000}\right)\right) < S_{max} \rightarrow F_t = 0 \end{cases} \quad (7)$$

Two issues should be addressed in this section as well. First, more details regarding the environmental flow regimes in the optimization model. Defining different protection scenarios in the environmental flow assessment is a known method for ecological assessment of the environmental flow. Assessment of the environmental flow is not in the scope of this research work. Thus, it was defined based on the previous ecological studies in the case study by the IFIM (Abdoli et.al, 2020). It should be noted that three issues including water quality and quantity and timing have been addressed in the IFIM. Two main protection levels were defined in the cited study including minimum protection level and ideal protection level. Based on these protection levels, two environmental flow regimes were presented including minimum environmental flow regime and ideal environmental flow regime. The minimum environmental flow regime might guarantee the minimum required habitat suitability for the biological activities of the fishes such as reproduction or searching for food. However, it might not provide the maximum required suitable area. Hence, the ideal environmental flow was defined in which habitat suitability is perfect.

Secondly, it should be addressed why monthly time scale was applied in the optimization of the environmental flow. Two points should be noted in this regard. First, many previous studies proposed monthly scale in the management and assessment of the environmental flow. Moreover, management of the environmental flow in the daily scale might not be practical in the reservoir management due to technical limitations for controlling release day by day. This time scale might not be perfect to protect the aquatic habitats. However, it is able to protect average habitat suitability that might be acceptable in the long-term management of the environmental impacts.

### 8.5.4 Evolutionary algorithms

Evolutionary algorithms might not guarantee the global optimization for complex objective function such as reservoir operation function. Thus, using different algorithms and measuring their performance for selecting the best algorithm might be necessary. Six different algorithms were utilized including genetic algorithm (GA) (Whitley, 1994), particle swarm optimization (PSO) (Kennedy and Eberhart, 1995), simulated annealing algorithm (SA) (Kirkpatrick, 1984), differential evolution algorithm (DE) (Qin et.al, 2008), biogeography based optimization (BBO) (Simon, 2008) and bat algorithm (BA) (Yang and Gandomi, 2012). A wide range of algorithms were applied including classic and new generation and animal and non-animal inspired algorithms. Steps of these algorithms are generally the same including initialization, parameter/population updating, fitness function evaluation, and criteria to stop.

However, they might use different strategies to find the best solution. More details regarding each algorithm are available in the cited references.

### 8.5.5 System performance measurement and decision-making system

The system performance was measured in terms of reliability, vulnerability and mean absolute error. More details on the measurement indices for the reservoir operation have been addressed in the literature (Hashimoto et.al, 1982). Three aspects were considered in this research work including environmental flow supply, water supply and storage loss. Developed mathematical forms of these indices are shown in the equations 8 to 11. Reliability and vulnerability indices were utilized for measuring environmental flow loss. Moreover, reliability index and mean absolute error (MAE) were used for measuring water supply loss and storage loss respectively.

$$Reliability\ index(water\ supply) = \frac{\sum_{t=1}^{T} R_t}{\sum_{t=1}^{T} D_t} \tag{8}$$

$$Reliability\ index(environmental\ flow) = \frac{\sum_{t=1}^{T} E_t}{\sum_{t=1}^{T} E(target)_t} \tag{9}$$

$$Vulnerability\ index(environmental\ flow) = Max_{t=1}^{T}\left(\frac{E(target)_t - E_t}{E(target)_t}\right) \tag{10}$$

$$MAE_S = \frac{\sum_{t=1}^{T} |S(optimum)_t - S_t|}{T} \tag{11}$$

Due to inability of the evolutionary algorithms for guaranteeing the global optimization, it is necessary to apply a robust decision-making system to select the best optimization algorithm. The fuzzy Technique of Order Preference Similarity to the Ideal Solution (FTOPSIS) is a robust decision-making system to select the best candidate based on the measurement indices. A hierarchical structure is used to make decision in this method including goal of the decision-making system, criteria and alternatives. In this research work, goal of the decision-making system is to select the best optimization algorithm. Criteria are system performance indices and alternatives, or candidates are optimization algorithms. Finally, alternatives are ranked based on the Closeness coefficient (CC). This coefficient is defined based on the equation 12 in which $d_i^+$ and $d_i^-$ are distance of each alternative from the fuzzy positive-ideal solution (FPIS,A+) and fuzzy negative-ideal solution (FNIS,A−) respectively. More details regarding FTOPSIS method are available in the literature (Chen, 2000).

$$CC_i = \frac{d_i^-}{d_i^- + d_i^+} \quad \text{i=1,2,…,m (the number of each alternative)} \tag{12}$$

### 8.5.6 Results

First, results of rainfall-runoff modelling are presented. Figure 8-5-2 displays the results of the SWAT calibration for monthly inflow of the Latian reservoir. As discussed in the previous section, calibration coefficients were adopted for simulation of stream flow in the river basin. According to the figure 8-5-2 that is output of the SWAT-CUP based on the SUFI2 method, developed runoff model is reliable. NSE is close to 0.5 that corroborates the reliability of the runoff routing model. According to the literature, If NSE is close to 0.5 or more than 0.5, model will have proper predictive skills. Figure 8-5-3 displays results of the validation period in which NSE is 0.57 that indicates robustness of the rainfall-runoff model as well.

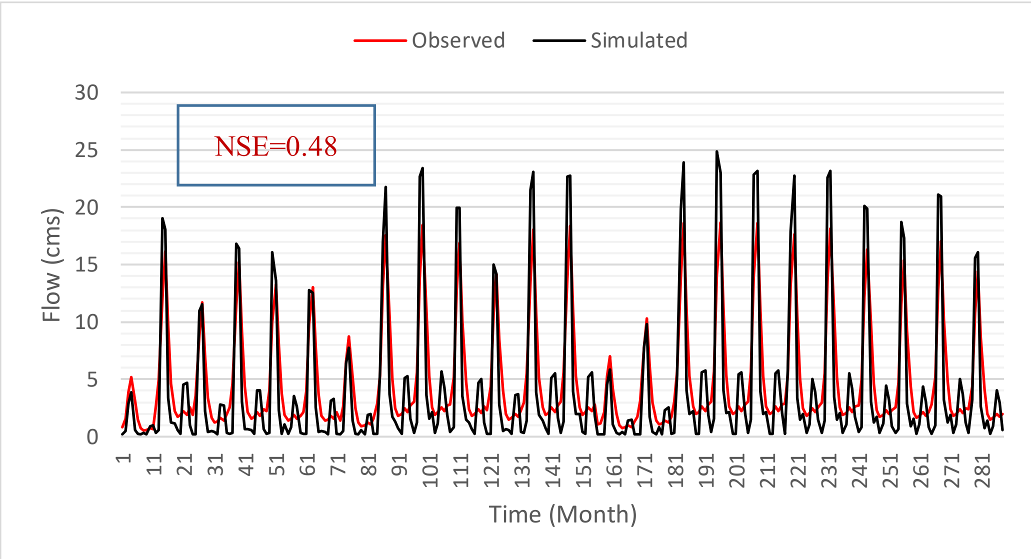



**Figure 8-5-2- Result of calibrating SWAT in 300 months as calibration period**

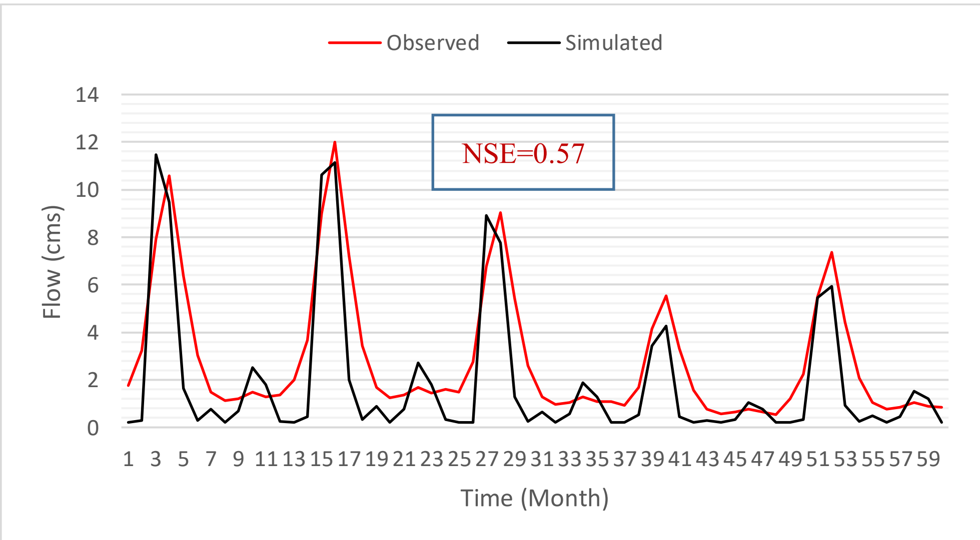



**Figure 8-5-3- Result of validating SWAT in 60 months as validation period**

As presented in the previous section, 50 months period of the validation period was selected as the simulation period for reservoir operation optimization. Inflows by other tributaries were simulated and added to the reservoir inflow. Moreover, additional flow from another river by the tunnel is conveyed to the Latian reservoir that was considered in the simulation of the reservoir inflow. Figure 8-5-4 displays total inflow of the Latian reservoir. Furthermore, minimum environmental flow regime and ideal environmental flow regime are displayed in this figure. Figure 8-5-5 displays inflow of the Mamloo reservoir that is not included environmental flow at downstream of the Latian reservoir. In other words, environmental flow regime at downstream of the Latian reservoir is the inflow of the downstream reservoir. This issue was considered in programming of optimization model.

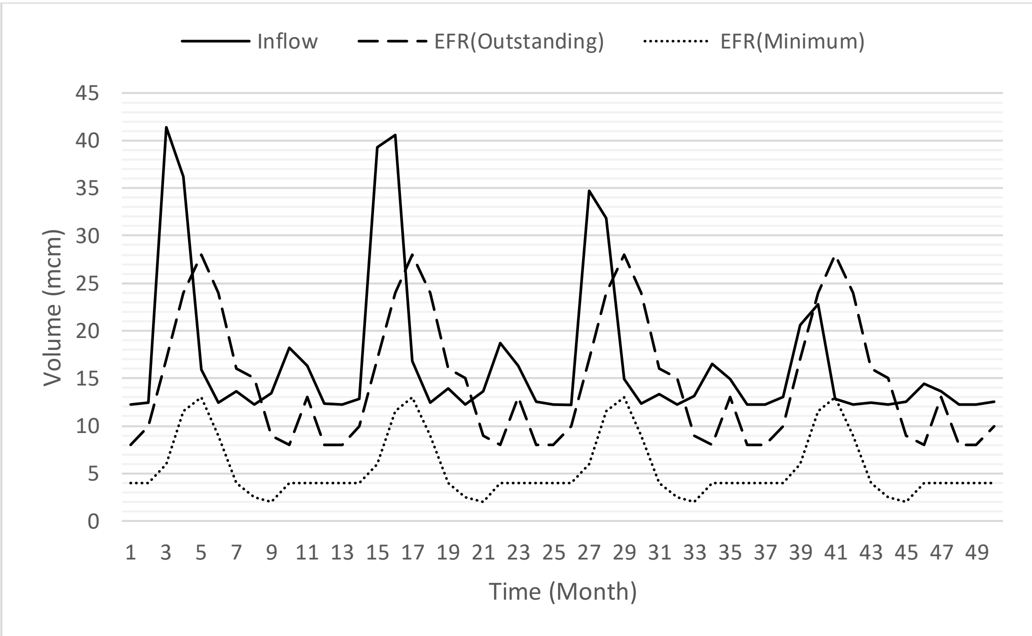



**Figure 8-5-4- Time series of total inflow, environmental flow for poor ecological status EFR (min) and environmental flow for outstanding ecological status EFR (outstanding) for Latian reservoir as upstream reservoir in simulated multi reservoir system**

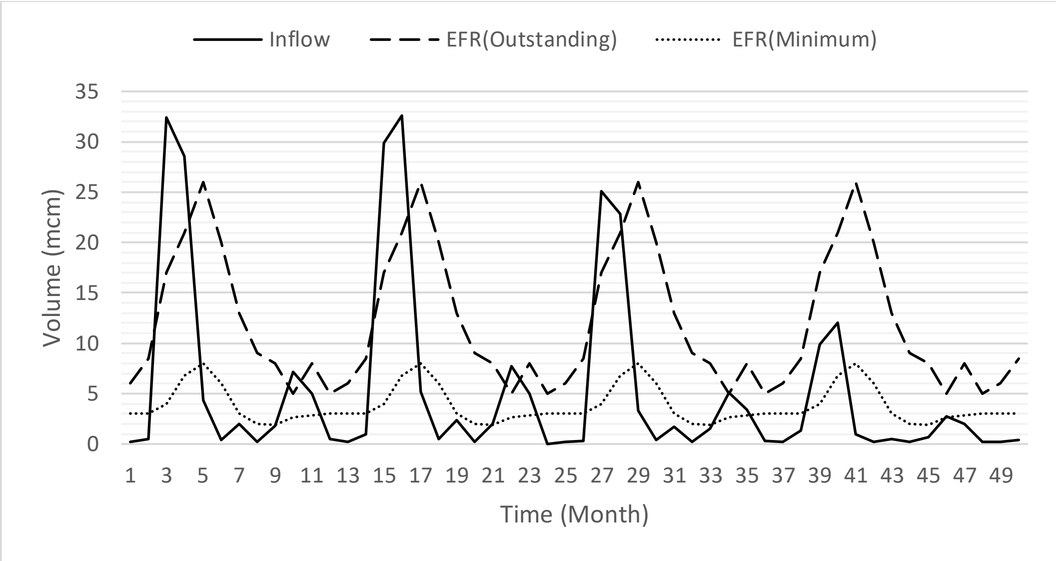
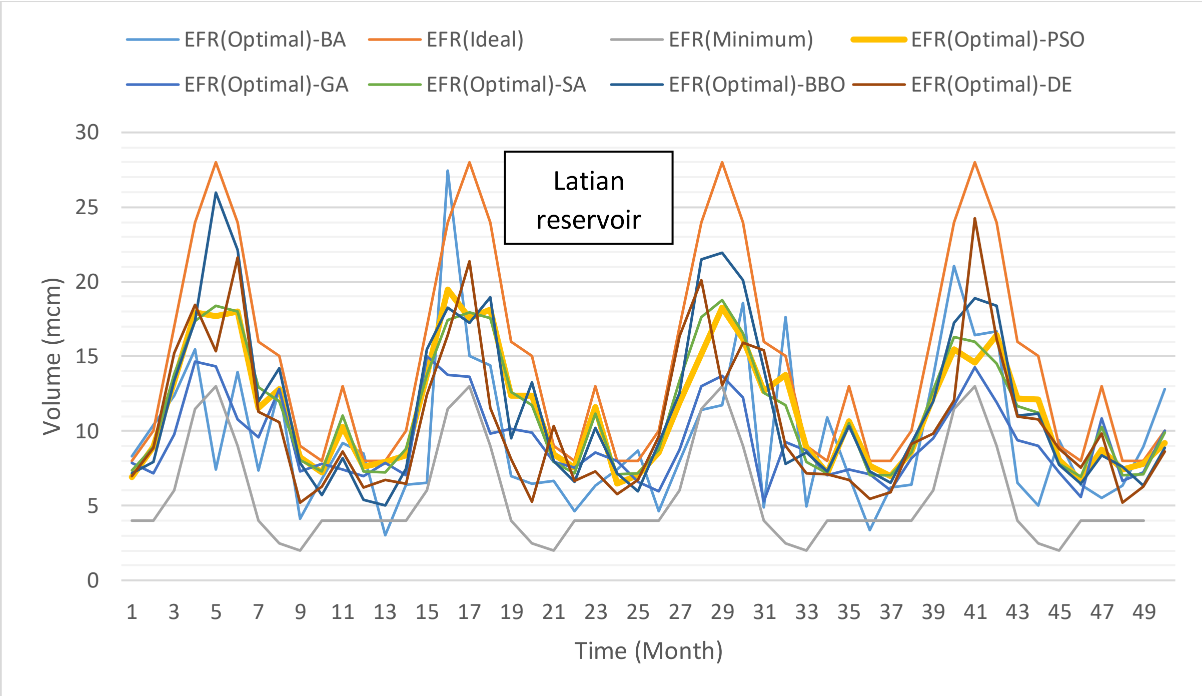



**Figure 8-5-5- Time series of inflow excluding environmental flow release from Latian reservoir, environmental flow for poor ecological status EFR (min) and environmental flow for outstanding ecological status EFR (outstanding) for Mamloo reservoir as downstream reservoir in simulated multi reservoir system**

Figure 8-5-6 displays the optimal environmental flow regime proposed by different algorithms for both reservoirs. Moreover, ideal and minimum environmental flow regimes have been displayed to compare outputs by the algorithms with defined flow regimes. Some algorithms such as PSO, GA and SA could protect minimum environmental flow regime properly in the case study. In other words, performance of the minimum environmental flow regime penalty function was robust in these algorithms. In contrast, the performance of BA and DE was not robust regarding the minimum environmental flow regime. In fact, the proposed optimal regime by these algorithms is less than minimum environmental flow regime in some time steps. It seems that BA is the weakest algorithm in this regard. More investigation on the performance of the algorithms in terms of optimal environmental flow regime needs computation of the system performance indices.

Figure 8-5-7 displays storage of the reservoirs during the simulated period. It seems that the performance of some algorithms is similar. For example, performance of BA and PSO is similar in terms of storage in the Mamloo reservoir. However, results demonstrate that the performance of algorithms might be different in terms of storage. Hence, using the best algorithm to optimize reservoir operation is essential. Utilizing measurement indices in terms of storage seems necessary as well. A point should be noted regarding the supply of water demand by these reservoirs. Given the possibility of the secondary storage, total supplied water demand is important in this basin. Hence, the reliability index was used to measure the system performance in terms of water supply loss. Table 8-5-1 displays measurement indices of the optimization system. Moreover, figure 8-5-8 shows final ranking of the optimization algorithms by the FTOPSIS method.



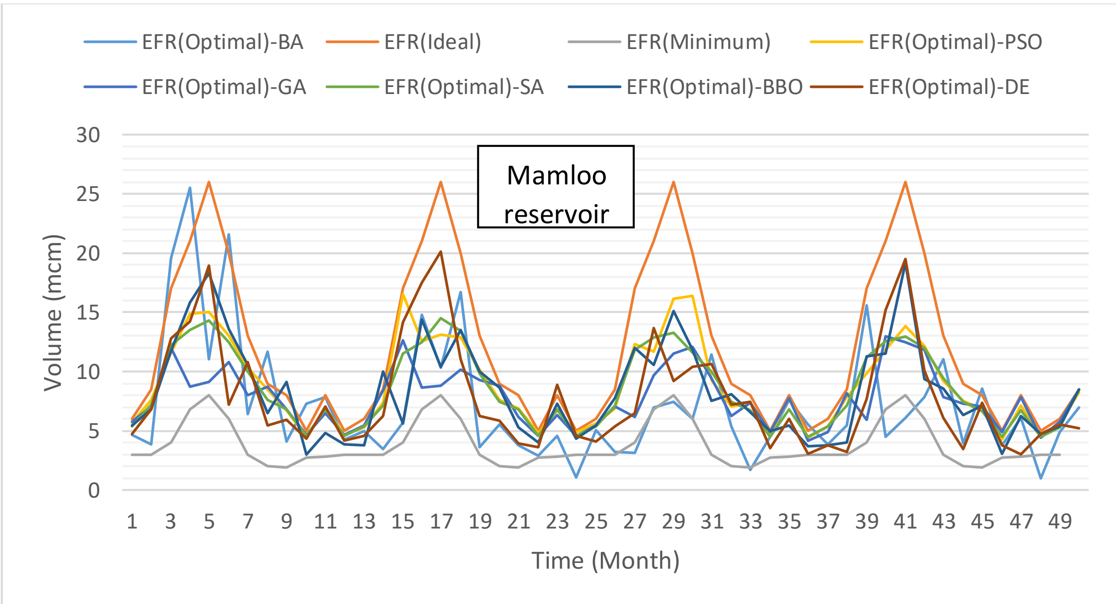
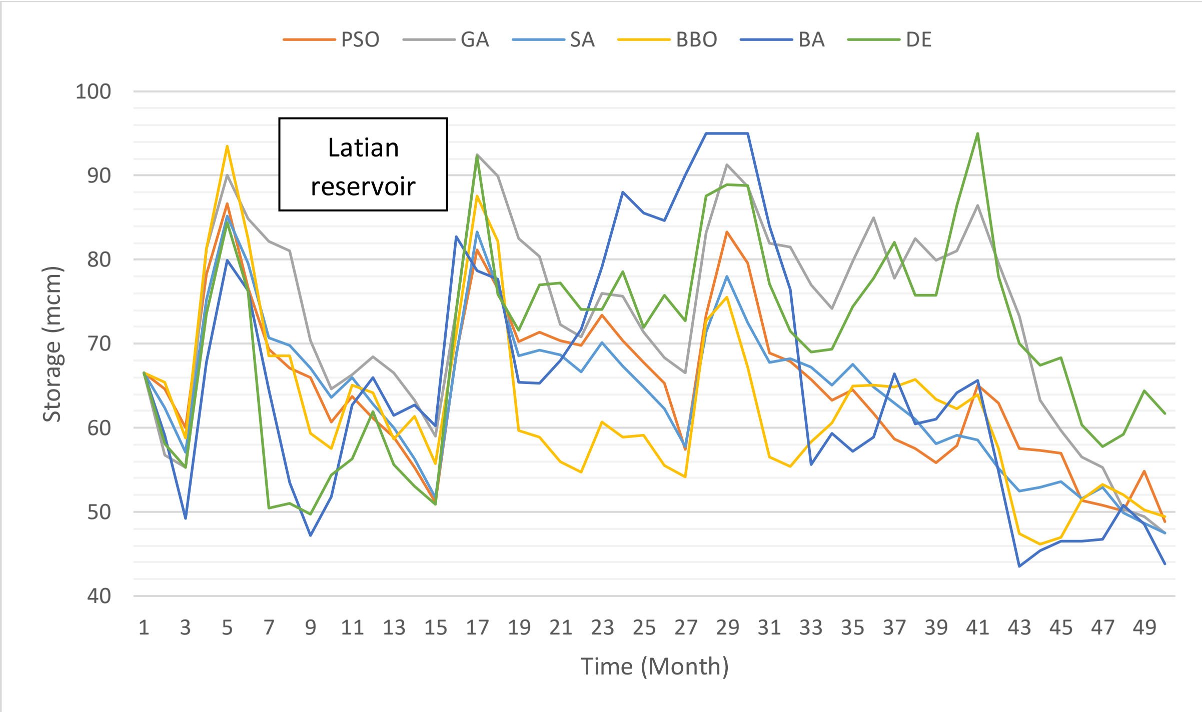




**Figure 8-5-6- Optimal environmental flow regime in the multireservoir system**



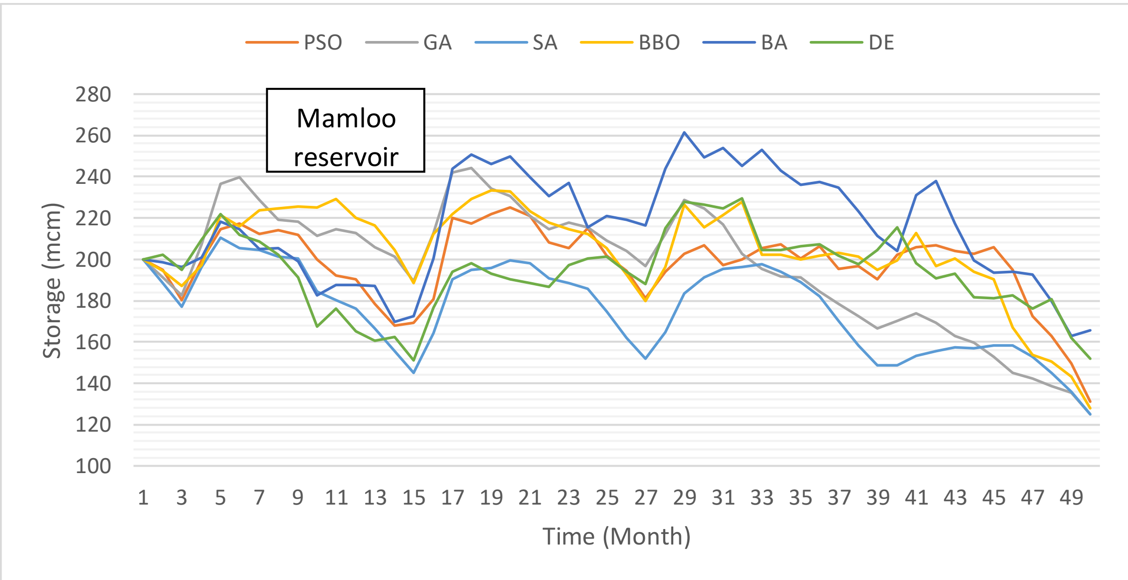




**Figure 8-5-7- Storage time series in the reservoirs during simulated period**

**Table 8-5-1- Results of system performance analysis**

| | Reliability index (environmental flow) | | Reliability index (water supply) | | Vulnerability index (environmental flow) | | Mean absolute error (Storage) | |
|---|---|---|---|---|---|---|---|---|
| | Latian | Mamloo | Latian | Mamloo | Latian | Mamloo | Latian | Mamloo |
| PSO | 0.77 | 0.74 | 0.26 | 0.24 | 0.48 | 0.50 | 11.63 | 12.99 |
| GA | 0.63 | 0.65 | 0.35 | 0.21 | 0.67 | 0.66 | 9.64 | 24.24 |
| SA | 0.77 | 0.71 | 0.26 | 0.25 | 0.43 | 0.50 | 12.01 | 24.73 |
| BBO | 0.79 | 0.69 | 0.24 | 0.26 | 0.48 | 0.67 | 14.77 | 17.44 |
| BA | 0.65 | 0.60 | 0.33 | 0.21 | 0.73 | 0.81 | 14.99 | 24.57 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| DE | 0.72 | 0.66 | 0.27 | 0.23 | 0.65 | 0.65 | 9.64 | 15.11 |

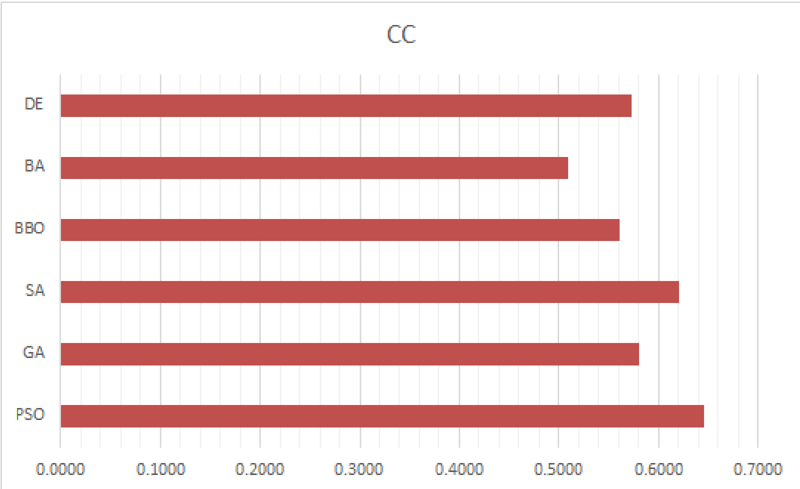



**Figure 8-5-8- Final ranking of optimization algorithms based on closeness coefficient**

### 8.5.7 Discussion

A full discussion on the results of the optimization system is needed. According to the table 8-5-1, measurement indices properly indicate the performance of the optimization model. First, the robust performance of the optimization system in both reservoirs in terms of reliability index of the environmental flow regime should be noted. In fact, minimum reliability index of the environmental flow is 60% that demonstrates 60% of the ideal environmental flow regime as the target of the optimization model could be supplied. It should however be noted that some algorithms such as BBO,PSO and SA are more robust in this regard in the case study. In fact, they can supply 80% of the ideal environmental flow in the simulated period approximately. Hence, these algorithms are in priority in terms of reliability of environmental flow regime. However, measuring the system performance regarding other effective factors is necessary to evaluate and select the best optimization algorithm.

Supply of water demand is another aspect for evaluating the optimization methods. As discussed in the previous section, these reservoirs are not the only water resources for supply of defined water demands. Hence, full water supply is not expected for both reservoirs. In fact, it matters that reservoirs supply water demand as much as possible. Result of the optimization might be helpful for management of the water resources. Reliability index is the best index to measure the water supply loss. It indicates how much water could be supplied in the simulated period. The performance of different algorithms is not the same for the reservoirs that demonstrates that optimization of the multiresevoir systems in an integrated framework to design optimal environmental flow regime is essential. Either GA or BA has the most robust performance for water supply in the Latian reservoir. However, either SA or BBO has the highest reliability for water supply in the Mamloo reservoir. According to the results, 25% to 30% of the total defined maximum water demand for each reservoir could be supplied.

Another important measurement index is vulnerability index for environmental flow regime. This index indicates the maximum vulnerability in the simulated period. Not only reliability of the environmental flow supply is important in the evaluation of the system, but also vulnerability index is such effective as well. In other words, if required environmental flow demand could not be supplied in each time step or each month, it might reduce suitability of the habitats regardless of annual supply. Based on the results, the difference between optimization methods might be considerable. Minimum vulnerability index is 40%. However, its maximum is 80% that demonstrates a remarkable difference between the optimization methods in terms of vulnerability of environmental flow regime. Hence, selecting the best evolutionary method to optimize environmental flow regime might be very important. Interestingly, trend of the different methods is close that means their performance in the both reservoir is similar. SA is the best method that has the lowest vulnerability in the case study. However, either PSO or BBO are robust regarding vulnerability in the case study as well. The results reveal that applying a single optimization method or algorithm might not reliable for designing the optimal environmental flow regime. For example, the weak performance of BA indicates that it might not be robust method to optimize environmental flow regime in the case study. Using different methods might be helpful to design the optimal flow regime.

Benefits from the storage in each reservoir must be taken into account as an important criterion to measure the system performance. Some benefits are dependent on the available storage in the reservoirs. In other words, storage loss or deviation from the optimum storage must be measured in an optimization system of the reservoirs. Based on the recommendations by regional water authority, 75 and 200 mcm were considered as the optimum storage of the Latian and Mamloo reservoirs respectively. Thus, mean absolute error (MAE) was computed based on the optimum storage in the reservoir. Less MAE indicates less deviation from the optimum storage of the reservoir. The performance of algorithms is different in terms of storage loss. For example, results of the Latian reservoir demonstrate that either DE or GA is the most robust methods to optimize storage benefits in the case study. Conversely, results of the Mamloo reservoir indicate that either DE or PSO is the best methods in terms of maximizing storage benefits in the case study.

System performance indices demonstrate that each algorithm might have different performance in terms of supply of environmental flow and water demand and storage loss. Hence, selecting the best method is not possible by observation of the results. In other words, using a robust decision-making system is necessary to select the best method. It should be noted that selecting the best optimization algorithm might be crucial. It would introduce the most efficient environmental flow regimes. FTOPSIS was used as the decision-making system to select the best method. Two aspects are such important regarding the application of FTOPSIS method including weights of importance and rating of alternatives. Chen, 2000 developed linguistic variables for the importance weight of each criterion consisting of very low to very high degree of importance. Four criteria were applied for each reservoir that means eight criteria were taken into account to make a right decision.

The weights of importance for vulnerability and reliability index of environmental flow were considered as very high and high respectively. Furthermore, reliability index for water supply and mean absolute error for storage loss were considered as very high and high respectively. As a description on the allocated weights, it should be noted two criteria were used to measure environmental flow performance. In contrast, one criterion was used to measure the water supply as well as storage benefits. Vulnerability index of environmental flow was considered as very high. It should be noted that lack of suitability of habitats in each time step might be very harmful for the regional ecological values. Moreover, reliability of the environmental flow regime was considered as high. In fact, it might not be as important as vulnerability index for simulated period. Furthermore, reliability index of water demand was considered as very high due to importance of supply of maximum water demand that might be a key purpose for the multiresevoir system in the study area. Moreover, the weight of importance of MAE is high due to less important compared with water supply by reservoirs. Another input to the FTOPSIS decision-making system is rating of the alternatives or candidates. Decision on rating of alternatives was made by overall opinion of decision makers who were authors of present study based on presented discussion on performance of measurement indices. PSO is the best method to optimize reservoir operation in the case study. Moreover, SA is the second proper optimization method in the case study. To sum up, utilizing these two algorithms in the case study to design optimal environmental flow regime is recommendable. It is recommendable to exclude other algorithms for solving defined objective function in the case study.

Discussion on the advantages and limitations of the proposed method is vital. Computational complexities are one of the most important limitations in the application of the optimization algorithms. In the computer science, computational complexities might be defined as the required time and memory to find the best solution by the optimization algorithm. Numerous simulations and covering a long-term period might be needed to apply the proposed framework in the practical projects. The proposed single objective function has low computational complexities that is a significant advantage for the proposed method. This form of the objective function is appropriate for the complex system in which high computational complexities might be problematic . Thus, aggregating objective functions in a single objective function is helpful to develop an efficient optimization model that might be applicable in the future studies.

It should be noted that different performance of the evolutionary algorithms is one of the important aspects in the optimization process by these algorithms. Due to inability of these algorithms for guaranteeing the global optimization, it is essential to apply different algorithms and compare the results to select the best solution for optimization problems especially in the complex models such as reservoir operation models. The major element of interest for the developed method is to present the fair comparison between many different evolutionary algorithms (in their single objective version), which is performed on a real-world case study. In fact, some key criteria were defined in the structure of the decision-making system to select the best response for the reservoir operation optimization in which different evolutionary algorithms should be applied to find the best solution. Development and improvement of the evolutionary algorithms are still a fresh and required research field. In fact, the main advantage of the proposed model is possibility of using a wide range of single objective algorithms that might be helpful to optimize reservoir operation considering complex tasks such as supply of the environmental flow regime. It should be noted that the outputs of this research work demonstrated the acceptable performance of the developed objective function in the reservoir operation. Thus, this form of the objective function is recommendable for the future studies in the reservoir operation.

Another question should be responded and discussed is why the weights of importance were set after application of the evolutionary algorithm in the optimization process. In the ideal condition, it is expected to obtain the global optimization by all the algorithms. Thus, it is not needed to apply the decision-making system or to set importance criteria in the optimization model. In fact, the global optimization provides the perfect performance in terms of all the technical aspects. However, evolutionary algorithms cannot guarantee the global optimization for the complex objective function such as reservoir operation function. Thus, it is needed to compare results for selecting the best solution. In the multipurpose reservoir, defining weights of importance is based on the technical considerations in each case study and it might be different case by case. In the case study, they are assumed based on the technical considerations. Using FTOPSIS and the described strategy might be helpful for increasing the flexibility in the management of the reservoir to select the best solution considering regional challenges. For example, supply of water demand might be more important than supply of environmental flow in a case study for the managers. It is recommendable to set weights by negotiations between the stakeholders and the environmental managers.

PSO was selected as the best method in the case study. However, it is not claimed that this algorithm is the best algorithm for all the cases. In fact, the weights of importance were selected based on the technical considerations in the case study. Thus, it might be changed in other case studies. Moreover, altering the structure of the optimization in the future studies might change the performance of the evolutionary algorithms. Hence, it is recommendable to use the decision-making system in each case study independently.

Another important aspect is advantages and strengths of the proposed methods compared with previous frameworks in the reservoir operation optimization. Conventional optimization model of the reservoir operation did not consider environmental flow in the optimization model. The proposed method is helpful for improving the structure of the optimization to minimize environmental impacts of the reservoir. Some recent studies considered minimum environmental flow regime as the fixed time series in the optimization model. In other words, one release was taken into account by guaranteeing the Minimum Environmental Flow (MEF). Old methods of the environmental flow assessment recommend the minimum environmental flow for the river. However, advanced holistic methods highlight that the minimum environmental flow could not guarantee the appropriate ecological status for the river ecosystem. In fact, defining environmental flow regime should be carried out in an optimization process in which two main protective ecological scenarios including ideal ecological status (equivalent to ideal environmental flow regime) and poor ecological status (equivalent to minimum environmental flow regime) are considered. It is excellent to supply the ideal environmental flow regime. However, it might increase the water supply loss and storage loss in some time steps considerably. Hence, a simultaneous optimization system for water supply and environmental flow is favorite for getting the best results in the reservoir operation. It should be noted that minimum environmental flow has been guaranteed in the proposed framework by defining the penalty function. However, it might not provide the ideal ecological status. Optimization model increases the release for obtaining the ideal environmental flow regime as the target of the system. In fact, this research work provided a novel form of the optimization model in which minimum environmental flow regime has been changed to the optimal environmental flow regime that might guarantee the suitable ecological status in the river ecosystem based on the defined protective scenarios by the IFIM. This strategy is helpful to increment environmental flow regime as much as possible while water supply and storage loss are mitigated. The proposed method might provide a fair balance between environmental requirements and water demands. Thus, it is strongly recommendable to consider two variables including release for water demand and release for environment in the future studies of the reservoir operation in which two environmental flow regimes should be defined based on the protective scenarios. In our case, release for water demand is being pumped directly from the reservoirs.

Integrating benefits of the reservoir and environmental impacts in one model might reduce negotiations between the environmental managers and the stakeholders. The most important strength of the developed model compared with the previous studies is to consider a novel and applicable strategy to define environmental flow regime in the optimization model considering minimum environmental flow regime in the penalty function and ideal environmental flow as the target of the optimization model. In other words, two different protection scenarios are useable in the structure of the optimization model. Moreover, the proposed method is upgradable and flexible that means outputs of other holistic methods of the environmental flow assessment could be used for defining minimum and ideal environmental flow regime. Due to impact of climate change on the stream flow, it is recommendable to add the climate change models to the developed framework for investigating the impact of climate change on the supply of environmental flow regime and water demand. In fact, this combination might be helpful for facing the future challenges in the management of the river ecosystems. Moreover, increasing population might be another challenge in the environmental management of the river basins. Hence, it might be interesting to add the population projection models to the proposed framework for optimizing the environmental flow in the multireservoir systems.

As a summary of this section, we proposed an integrated framework to optimize environmental flow regime at downstream of the multireservoir systems. Soil and water assessment tool (SWAT) was used to simulate inflow of the reservoirs. Results indicated that using coupled SWAT-SWAT CUP model to simulate and calibrate monthly inflow of reservoir is a robust method that could be utilizable in the future studies. The performance of the inflow model was measured by the Nash-sutcliffe efficiency (NSE). NSE was close to 0.5 that demonstrates the appropriate predictive skills for the stream flow model. Moreover, Different evolutionary algorithms were applied to optimize the reservoir operation. The performance of the optimization model was measured in terms of supply of environmental flow regime, supply of water demand and storage loss. FTOPSIS was utilized for selecting the best solution. Results indicated that PSO is the best method to optimize environmental flow regime in the case study. Reliability of the environmental flow supply was approximately 80%. Furthermore, vulnerability index of environmental flow was 40% approximately. SA was the second acceptable optimization method in the case study. Low computational complexity is one of the advantages of the proposed method.

## *8.6 Linking environmental flow optimization and economic benefits of reservoirs (Framework 6)*

### 8.6.1 Overview on the methodology

It might be helpful to have an overview on the methodology that is displayed in the figure 8-6-1. As the summary of the methodology, the environmental optimization model of the reservoir operation and cropping pattern optimization are coupled to maximize economic benefits of the reservoir including hydropower production and food production revenue. The proposed method converts a conventional reservoir operation optimization to a novel optimization model of the reservoir operation in which the food production revenue, hydropower production and ecological modelling of the river ecosystem are linked. Three questions should be responded in this section including 1-how the study was designed? 2-how the study was carried out? And 3-how the data were analysed? The study was designed based on an actual project of the reservoir operation in which environmental degradations and negotiations between stakeholders and environmental managers were a challenging issue that needs an integrated optimization system. This system should be able to provide interest of the farmers, electrical energy users and environmental managers simultaneously. The study was carried out by some field studies in the river ecosystem, defining a proper objective function and solving the optimization system by the appropriate optimization methods. The generated results of the model were analysed based on some measurement indices to evaluate the abilities of the optimization model

Ecohydrualic simulation is one of the requirements in the developed model in which using results of the field studies might be essential. Moreover, drought analysis is carried out to develop monthly flow time series in the dry years, normal years, and wet years. Three outputs of the optimization model include optimal ecological flow, maximum hydropower production and maximum food production revenue. The cropping pattern optimization was utilized to maximize food production revenue. Finally, some indices were applied to measure the performance of the optimization system. More details regarding each section of the framework are presented in the next sections.

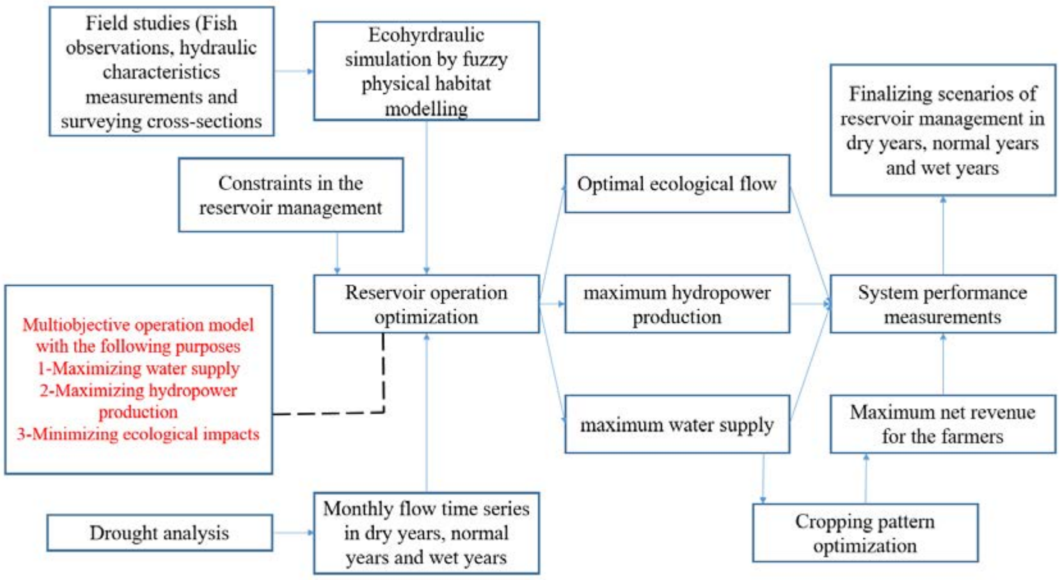



**Figure 8-6-1- Workflow of the proposed method**

## 8.6.2 Ecohydraulic simulation

We applied the fuzzy physical habitat simulation as the efficient method for ecohydraulic simulation in which three main tasks should be carried out. In the first step, a combination of fish observations and expert opinions were applied to develop verbal fuzzy rules for the habitat suitability of the selected target species in the study area. Then, 1D hydraulic simulation by the HEC-RAS 1D was used to simulate depth and velocity distribution for different flows in the representative reach. Finally, results of the hydraulic simulation and verbal fuzzy rules were combined to compute weighted useable area in different flows. The normalized weighted useable area function was applied as the environmental impact function in the reservoir operation model. More details are available in chapter 4.

It is required to describe the field studies in the case study as well. The field studies include fish observations and hydraulic studies in which fish sampling and measuring hydraulic characteristics might be carried out. Several direct and indirect methods have been proposed for fish sampling in the literature (Harby et.al, 2004). Each method might have some advantages and disadvantages. We applied the electrofishing method that is a known method for fish sampling. One of the drawbacks of this method might be high voltage that is detrimental for the fishes. However, we reduced the voltage as much as possible for recovering the fishes. As a full description on the on-site survey, the following steps were carried out

1- The cross sections were surveyed by the conventional methods in which cross section profile was plotted that were applied in the 1D hydraulic simulation of the representative river reach to obtain depth and velocity distribution
2- Electrofishing was used in different points of the river reach in which shocked fishes were collected and biometry process was done out of the water for the selected target species
3- Depth was measured by the metal ruler for the habitats in which electrofishing was used.
4- Moreover, velocity was measured by the propeller using two-points method (measurement of velocity in 20% and 80% of the depth)
5- Substrate (bed particle size) was measured based on the sampling of the bed particles. Mean diameter was determined based on the image processing for the coarser particles and sieve analysis for the finer particles.

Results of biometry were utilized to develop verbal fuzzy rules of physical habitat suitability for the target species considering expert opinions. As a description on the development of the verbal fuzzy rules, an experienced hydroecologist developed fuzzy rules based on previous experiences regarding the target species in other rivers of the country. If each rule is compatible with the field observations, it could be used as the final rule. If the rule is not compatible with the field studies, then that rule could be changed based on the observations. As an example, one of the rules was defined as follows. Total number of rules was 27.

“If depth is high, velocity is high, and substrate is low then habitat suitability is low”

### 8.6.3 Drought analysis

Hydrologic condition might remarkably be effective on the water supply and hydropower or food production revenue by the reservoirs. Thus, a smart management of the reservoir should consider hydrological conditions in the scenarios of the reservoir operation. Generally, three hydrological conditions are identified in the river basins including dry years, normal years and wet years. In this research work, we used drought analysis to identify hydrological conditions in a long-term period at the upstream catchment of the reservoir. Then, monthly flow time series were computed in dry years, normal years and wet years as the input of the optimization model. More details regarding the drought analysis are presented as follows.

We utilized stream drought index (SDI) that is a known index to analyse drought condition in the streams. First, it is necessary to collect data for generating time series of monthly flow. Then cumulative stream flow volume should be calculated as displayed in the equation 1.

$$V_{i,k} = \sum_{j=1}^{3k} Q_{i,j} \quad i = 1,2,\dots,12 \quad k = 1,2,3,4 \tag{1}$$

where K means period of drought analysis (three to twelve months). In the next step, it is required to utilize equation 2 for computing SDI.

$$SDI_{i,k} = \frac{v_{i,k} - V_k}{s_K} \quad i = 1,2,\dots,12 \quad k = 1,2,3,4 \tag{2}$$

where V and S are mean and standard deviation of cumulative stream flow volume respectively. More details regarding stream drought index have been addressed in the literature (Akbari et.al, 2015). Table 8-6-1 displays defined criteria to determine a year as non-drought to extreme drought (Akbari et.al, 2015).

**Table 8-6-1- Criteria for definition of SDI**

| State | Description | Criterion of SDI |
|---|---|---|
| **0** | Non-drought | =<0.0 |
| **1** | Mild drought | -1.0=> and <0.0 |
| **2** | Moderate drought | -1.5=> and <-1.0 |
| **3** | Severe drought | -2.0=> and <-1.5 |
| **4** | Extreme drought | <-2.0 |

We utilized 12 months SDI to determine hydrological status in the river including dry years, normal years and wet years. Then, we considered years with status of moderate to extreme drought as the dry years, and mild drought as the normal years and other values as the wet years.

### 8.6.4 Reservoir operation optimization

The objective function is the main component in each optimization model that should be defined based on the initial purposes of the model. In this research work, three purposes were considered including maximizing irrigation supply, maximizing hydropower production and minimizing ecological degradations at downstream river habitats. Equation 3 displays novel objective function of the reservoir operation developed in this research work where $D_t$ is maximum water demand, $R_t$ is release for water supply, $PP_t$ is hydropower production. Moreover, PPC is maximum hydropower production based on the capacity of the installed power plant, $NNWUA_t$ is normalized weighted useable area in the natural flow and $ONWUA_t$ normalized weighted useable area in the optimal environmental flow.

$$Minimize(OF) = \sum_{t=1}^{T}(\frac{D_t - R_t}{D_t})^2 + (\frac{PP_t - PPC}{PPC})^2 + (\frac{NNWUA_t - ONWUA_t}{NNWUA_t})^2 \qquad (3)$$

Hydropower production in each time step is computed based on the equation 4. As could be observed, release to the downstream and available head in the reservoir are mainly effective in the hydropower production. In the equation 4, E is generation efficiency of the reservoir, $H_t$ is reservoir water level at upstream of the turbine, $TW_t$ is outlet water level, PF is plant factor of the reservoir and $RE_t$ is release to the downstream. it should be noted that if $PP_t$ is greater than PPC as the installed capacity, PPC will be considered as the hydropower production in the time step t.

$$PP_t = \frac{RE_t.g.E.(H_t - TW_t)}{PF.1000} \qquad (4)$$

Each optimization system might require some constraints in the optimization process. In the reservoir operation problems, constraints of the reservoir management should be considered in the optimization model. Three technical constraints were inserted to the optimization model including release for hydropower production, release for water demand and storage constraints of the reservoir. Using penalty function method is one of the appropriate methods in the evolutionary optimization in which a constrained optimization problem could be converted to the unconstrained optimization problem. Some penalty function would be added to the optimization model that increase the penalty of the system due to violation of the defined constraints. The following penalty functions were added to the optimization system. $Q_{max}$ and $Q_{min}$ are maximum and minimum discharge for the power plant based on the initial design. C1 to C5 are constant coefficients that were determined based on the initial sensitivity analysis of the optimization model.

$$if S_t > S_{max} \rightarrow P1 = c1(\frac{S_t - S_{max}}{S_{max}})^2 \qquad (5)$$

$$if S_t < S_{min} \rightarrow P2 = c2\left(\frac{S_{min} - S_t}{S_{min}}\right)^2 \qquad (6)$$

$$if\ R_t > D_t \rightarrow P3 = c3\left(\frac{R_t - D_t}{D_t}\right)^2 \quad (7)$$

$$if RE_t > Q_{max} \rightarrow P1 = c4(\frac{RE_t - Q_{max}}{Q_{max}})^2 \quad (8)$$

$$if RE_t < Q_{min} \rightarrow P1 = c5(\frac{Q_{min} - RE_t}{Q_{min}})^2 \quad (9)$$

Storage should be updated in each time step (Monthly time step). Equation 10 carried out this responsibility in the proposed method. Moreover, overflow was computed by the equation 11. It should be noted that we used the particle swarm optimization (PSO) in the optimization process of the reservoir operation. More details regarding this evolutionary algorithm have been addressed in the literature. In the equation 10, TR is total release, S is storage, F is overflow, A is area of the reservoir and EV is evaporation from the surface of the reservoir.

$$S_{t+1} = S_t + I_t - TR_t - F_t - \left(\frac{EV_t \times A_t}{1000}\right), t = 1,2, \dots, T \quad (10)$$

$$\begin{cases} if\left(S_t + I_t - \left(\frac{EV_t \times A_t}{1000}\right)\right) \geq S_{max} \rightarrow F_t = S_t + I_t - \left(\frac{EV_t \times A_t}{1000}\right) - S_{max} \\ if\left(S_t + I_t - \left(\frac{EV_t \times A_t}{1000}\right)\right) < S_{max} \rightarrow F_t = 0 \end{cases} \quad (11)$$

## 8.6.5 Cropping pattern optimization

As presented, reservoir operation model might maximize the water supply at downstream of the reservoir. However, maximizing water supply might not be able to maximize the food production revenue. In the case study, supplied water is consumed to grow the crops at the downstream farms of the reservoir. Different strategies might be applicable regarding maximizing food production revenue in the agriculture. One of the applicable solutions that might be helpful is the cropping pattern optimization. Linear programming is one of the appropriate methods in the cropping pattern optimization. The previous studies demonstrated high efficiency for this approach (Osama et.al, 2017). It should be noted that linear programming might not be efficient in the water resources problems such as reservoir operation due to complexities of the function. However, the cropping pattern might not have complex objective function in a simple form. Equation 12 and 13 display the objective function of the cropping pattern optimization and required constraints respectively. It should be noted that we defined objective function based on maximizing net revenue for the farmers. In other words, maximizing of the net revenue is the most favourite scenario for the farmers. Hence, defining the food production revenue optimization based on the maximizing net revenue in the cropping pattern seems logical. In the equation 12, x is area of the cultivated crop (Ha) as the main variable in the optimization model. Y is yield of the crop in the study area (kg/Ha), FE is price of the crop ($) and CO is cost of the cultivation for the crop

(\$/Ha) and J is number of the selected crops. In the equation 13, MinCA is minimum cultivated area for the crop and MaxCA is maximum cultivated crop.

$$Maximize(net\ revenue) = \sum_{j=1}^{J}(x_j.Y_j.FE_j) - (x_j.CO_j) \qquad (12)$$

$$Cons1 \rightarrow MinCA_j \leq x_j \leq MaxCA_j$$

$$Cons2 \rightarrow Sum(x) \leq Total\ area \qquad (13)$$

$$Cons3 \rightarrow Total\ irrigation\ demand \approx Total\ available\ water$$

### 8.6.6 Measuring the system performance

Each optimization model needs some indices to measure the performance of the system. It is essential to investigate how the optimization system is able to support the defined purposes. These indices should be defined based on the requirements and technical consideration in the case studies. Based on the technical issues in the case study, three indices were considered to measure the performance of the optimization system. Reliability index was utilized to measure the performance of the system in terms of hydropower production. Moreover, RMSE was utilized to measure the robustness of the optimization system in terms of physical habitat loss. It should be noted water is mainly utilized for irrigation in the farms. Hence, measuring the performance of the cropping pattern model was applied for assessing food production revenue. Reliability index was used in this regard as well. The following equations show the defined indices to measure the performance of the optimization system.

$$RMSE_{Physical\ habitat\ loss} = \sqrt{\frac{\sum_{t=1}^{T}(NNWUA_t - ONWUA_t)^2}{T}} \qquad (14)$$

$$Relibility\ index_{Hydropower} = \frac{Total\ hydropower\ production\ by\ the\ reservoir}{Total\ power\ demand\ in\ te\ study\ area} \qquad (15)$$

$$Relibility\ index_{Net\ revenue} = \frac{Net\ revenue\ by\ the\ optimization\ model}{Maximum\ possible\ net\ revunue\ for\ the\ farmers} \qquad (16)$$

### 8.6.7 Case study

We implemented the novel optimization system at the Garan dam as one of the reservoirs in the Kurdistan province, Iran. The main economic activity at the downstream of this reservoir is agriculture. This constructed dam is mainly responsible for supply of irrigation demand in the study area. Moreover, hydropower plant is installed in the reservoir for hydropower production. Due to importance and sensitivity of water and energy supply in the study area, regional water authority needs to maximize benefits of the reservoir. In contrast, department of environment is willing to maximize environmental flow to minimize ecological impacts at downstream of the reservoir. Based on the initial ecological studies, several native fish species have been identified at downstream river of the reservoir that means protecting river habitats is essential. Figure 8-6-2 displays upstream river basin of the reservoir location of the dam and part of agricultural lands at downstream.

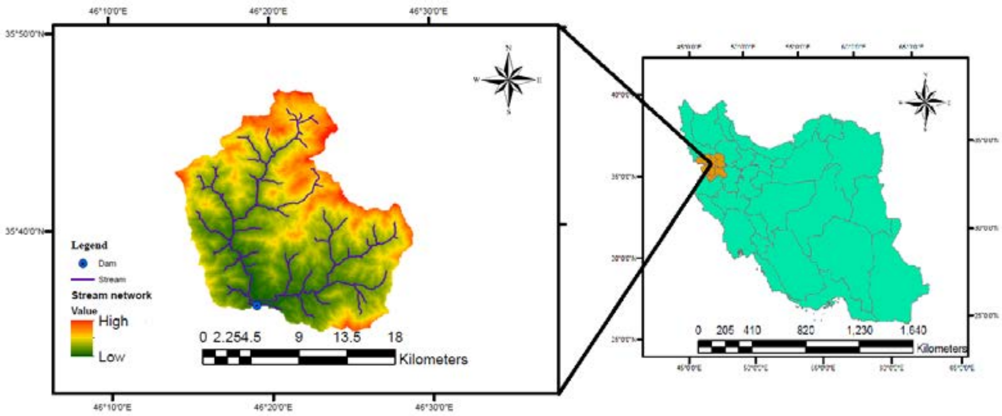



**Figure 8-6-2- Study area, location of Garan dam and upstream river basin**

Figure 8-6-3 displays price, yield, irrigation demand and minimum and maximum cultivated area for the selected crop in the study area.

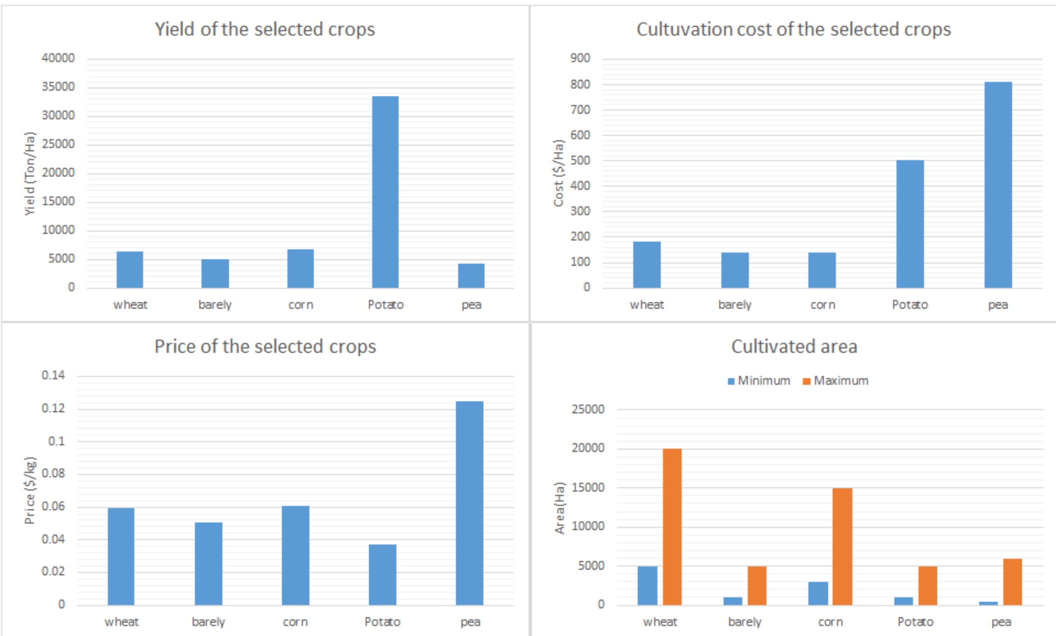



**Figure 8-6-3- More details on the selected crops in the optimization model**

## 8.6.8 Results and Discussion

Figure 8-6-4 displays drought analysis results in which stream drought index (SDI) in a long-term period has been assessed. It should be noted that SDI was computed based on the inflow of the reservoirs. It seems that study area might experience dry and wet years irregularly. According to the described methodology, mean monthly flows in dry, normal and wet years were calculated as displayed in the figure 8-6-5. The difference between dry years and wet years is considerable in some months. However, it is limited in other months. It sounds that the impact of hydrological condition on the available water in the reservoir is remarkable. Hence, assessing the role of the reservoir in the water-energy-food security nexus should be incorporating drought analysis to determine reservoir inflow in different hydrological conditions including dry years, normal years and wet years. In other words, we face a dynamic hydrological condition in the river basins that might be able to change loss of the reservoir operation as well as ecological condition at downstream river.

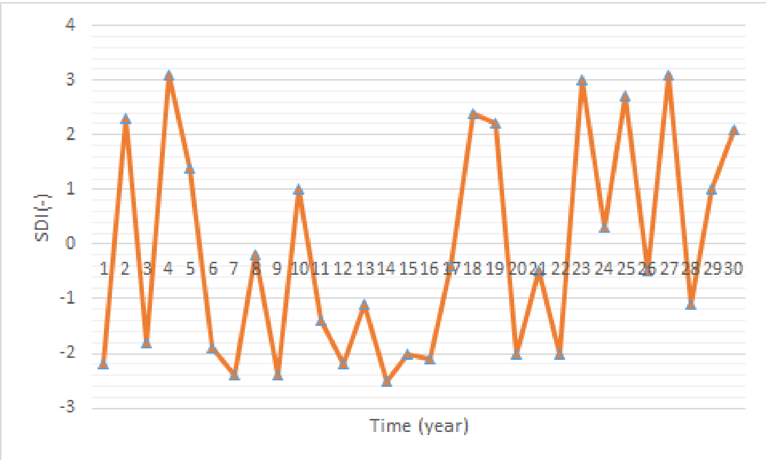



**Figure 8-6-4- Drought analysis results**

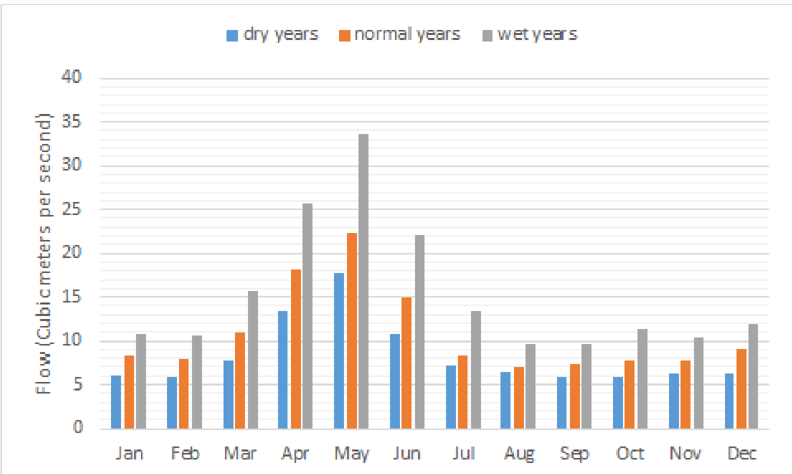


**Figure 8-6-5- Mean reservoir inflow in three hydrological condition including dry years, normal years, and wet years**

Normalized weighted useable area (NWUA) function is another output of the developed method. The final output of the fuzzy physical habitat simulation is NWUA function that could be utilized in the structure of the reservoir operation optimization to mitigate ecological impacts at downstream of the reservoir. A regression model was applied to finalize development of the ecological impact function as displayed in the figure 8-6-6. NWUA could be considered as the biological response of the river ecosystem for changing river flow. The biological response of the river ecosystem is not linear that means using ecohydraulic simulation is essential in the environmental assessment at downstream of the reservoir. Old methods of the environmental flow assessment such as hydrologic desktop methods considered a linear and direct relationship between the river flow and the biological response. In these methods, increasing river flow would enhance the habitat suitability in the river ecosystem. However, the output of the case study demonstrates that this assumption is not correct ecologically. Hence, we recommend utilizing ecohydraulic simulations as the reliable method to assess ecological impacts at downstream of the reservoir. It should be noted that correct assessment of the environmental degradation associated with the water-energy-food nexus might be very important due to its significant impact on the production in the river basins. The main purpose of this method is to maximize production by applying fewer resources. Hence, the incorrect assessment of the ecological impacts might negatively or positively affect the benefits from the reservoir. For example, if required environmental flow is assessed more than actual need of the river ecosystem, the irrigation supply might be considerably decreased that would lead to reduce benefits for the farmers as the stakeholders. Conversely, if the environmental flow is ecologically assessed less than actual need, the farmers' revenue will be increased. However, environmental degradation of the rive ecosystem will be increased as well. One of the advantages of the proposed method is to provide a correct ecological impact assessment in simulation of the reservoir operation.

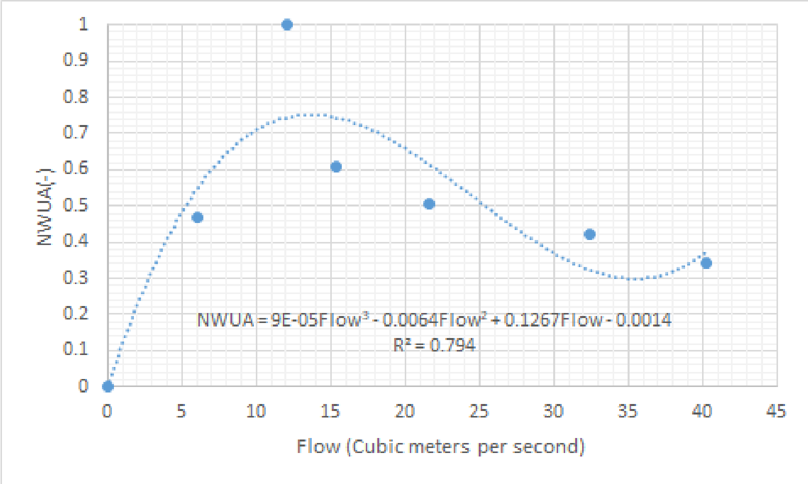



**Figure 8-6-6- Normalized useable area function as the main output of the fuzzy physical habitat simulation**

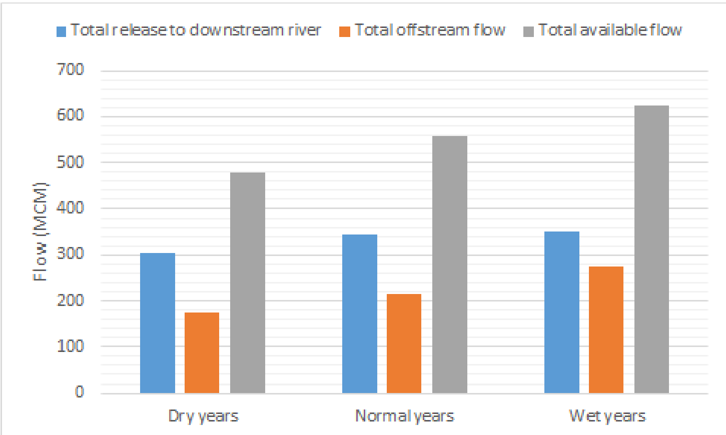



**Figure 8-6-7- Total offstream and release in the dry years, normal years and wet years.**

In the next step, it is necessary to present results of the optimization model as the main output of this research work. Figure 8-6-7 displays total instream flow (environmental flow) and offstream flow (water supply) for dry years, normal years and wet years proposed by the optimization model of the reservoir operation. It seems that environmental flow in different conditions is between 40% and 50% of the available flow in the river that means more than 50% of the available water could be utilized to supply water demand in the study area. It should be noted that instream flow in the case study could be used for either supply of environmental demand or hydropower production. Conversely, offstream flow is being pumped directly from the reservoir. Hence, allocated water as the instream flow and offstream flow is able to minimize ecological impacts at downstream river and maximize food and energy production by the reservoir. However, maximizing food production revenue might need cropping pattern optimization as the additional model to the proposed method.

In the next step, it is necessary to assess the performance of the optimization model in terms of physical habitat loss. We applied the NWUA function as the ecological impact function that means assessing physical habitat loss might be helpful to investigate how the optimization model is able to mitigate ecological impacts at downstream of the reservoir as one of the main purposes for the optimization system. Figure 8-6-8 displays NWUA in the natural flow and optimal environmental flow at downstream river of the reservoir. It should be noted that minimizing the difference between NWUA for the natural flow and NWUA for optimal environmental flow was considered as the purpose in the optimization system. If available suitable habitat area in the optimal environmental flow is close to the natural flow, it might guarantee the appropriate ecological status in the river. Based on the results, the proposed method is robust in terms of minimizing physical habitat loss in the study area. Interestingly, the optimization model is able to provide more suitable habitat area compared with the natural flow in the wet years due to non-linear relationship between flow and biological response. Moreover, the optimization model is able to minimize physical habitat losses in the dry years that might be a critical condition in the management of the reservoir. In the dry years, the inflow of the reservoir will drastically be decreased that means supply of environmental flow might be challenging in this period. In other words, conflict between supply of water demand and environmental flow is considerable in the dry years. It seems that robust performance of the optimization model in terms of physical habitat loss in the droughts could corroborate the applicability of the ecohydraulic simulation in the optimal management of the reservoirs.

In the next step, it is essential to investigate the output of the optimization system in terms of the hydropower production. Figure 8-6-9 displays the optimal normalized hydropower production in different hydrological conditions including dry years, normal years and wet years. It should be noted that we utilized the normalized hydropower production for better comparison of the impact of the hydrological condition on the optimal hydropower production in the case study. Clearly, the reservoir is able to provide the highest hydropower production in the wet years due to much available water in the river. In some months, reduction of hydropower production in the dry years is considerable that means droughts might be a serious threat for the hydropower production in the study area. However, the difference between dry years and wet years is not remarkable in some other months. Hydropower production is reduced 15% approximately in the normal years compared with the wet years. Furthermore, the hydropower production is decreased more than 30% in the dry years.

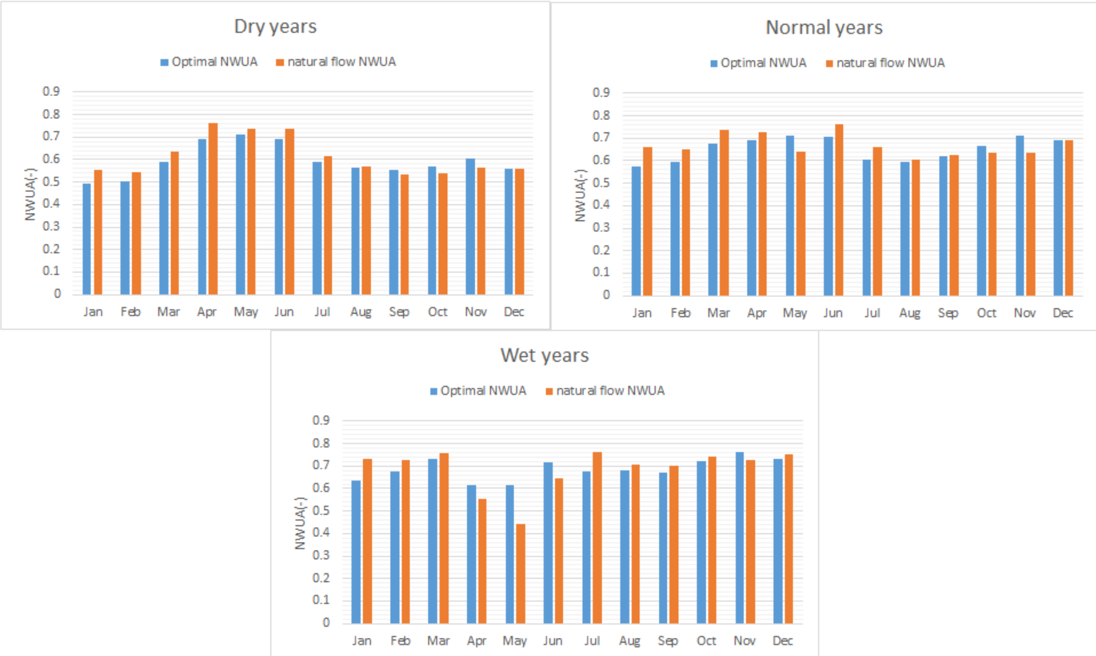



**Figure 8-6-8- Normalized weighted useable area in the natural flow and optimal environmental flow**

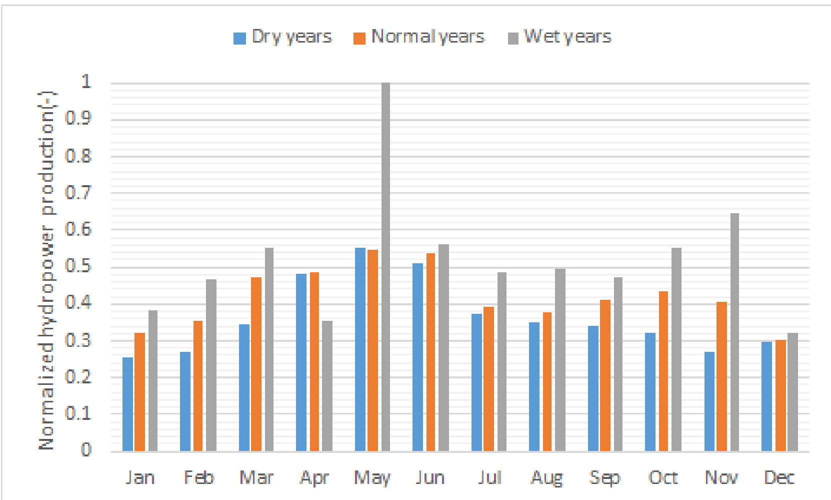



**Figure 8-6-9- Normalized hydropower production in dry years, normal years and wet years proposed by the optimization model**

In the next step, the result of the cropping pattern optimization should be presented. It should be noted that maximizing the food production is a purpose in the water-energy-food nexus approach. However, we considered the maximum net revenue in the cropping pattern optimization. At the first glance, it might be logical for considering the maximization of the food production revenue in the optimization model. However, it is not efficient method because costs of the cultivation should be taken into account in the optimal planning of the agriculture in the study area. In other words, if we ignore the costs of the cultivation, the proposed solution is not applicable. Hence, we recommend using the maximum net revenue in the optimization models of the food production revenue at downstream of the reservoirs. Figure 8-6-10 displays the optimal cropping pattern in the dry years, normal years and wet years. It should be noted that we considered the minimum and maximum cultivation area for different crops based on the recommendations by the regional agricultural department. It seems that the optimization model was able to find the optimal solution based on defined constraints. The optimization model mainly increases the area of the wheat in the available agricultural lands. However, the cultivated area of the corn is increased in the wet years as well. It seems that we should consider a dynamic cropping pattern in the study area. We considered some main crops in the optimization model. However, it is recommendable to simulate other types of the crops in the practical projects.

Measuring the performance of the optimization system is needed as well. As presented, we utilized three indices including reliability index for cropping pattern in terms of net revenue, reliability index for hydropower reproduction and RSME for physical habitat loss in the study area. Figure 8-6-11 displays these indices in the case study. It should be noted that reliability of the cropping pattern was compared with the maximum possible net revenue in the study area. The ideal net revenue means available net revenue for the farmers in the current condition without considering environmental flow regime at downstream of the reservoir. In other words, downstream release is used for other available agricultural lands and zero flow is available at downstream river habitats. Reliability index in the wet years is more than 50% that seems proper in the study area. It should be noted that supply of environmental flow would reduce the water supply that means considerable reduction of the food production revenue is predictable. However, the proposed optimization system is able to protect more than 50% of the revenue. In contrast, RMSE for the physical habitat loss is very low in all the hydrological conditions that means the optimization system is able to mitigate losses of food production revenue and ecological impacts simultaneously. At the first glance, it does not seem a fair balance between the environmental flow and water supply. However, it should be noted that sensitivity of the river habitats is much more important than the supply of the water demand or the food production revenue. The food production revenue could be enhanced using other available water resources in the study area such as ground water resources while alleviating environmental impacts in the river ecosystem is only possible by the instream flow that means other alternative water resources are not available to mitigate ecological impacts. Hence, we claim that the proposed optimal solution would provide a fair balance between the environmental requirement and water supply in the study area. Moreover, hydropower production was compared with the maximum needed electrical power in the study area. In the best condition (wet years), the reservoir is able to supply 25% of the needed power that means hydropower is not a reliable source for the energy supply in the study area. The reliability index of the hydropower reduces to 15% approximately in the dry years that means hydropower production might be critical in dry years.

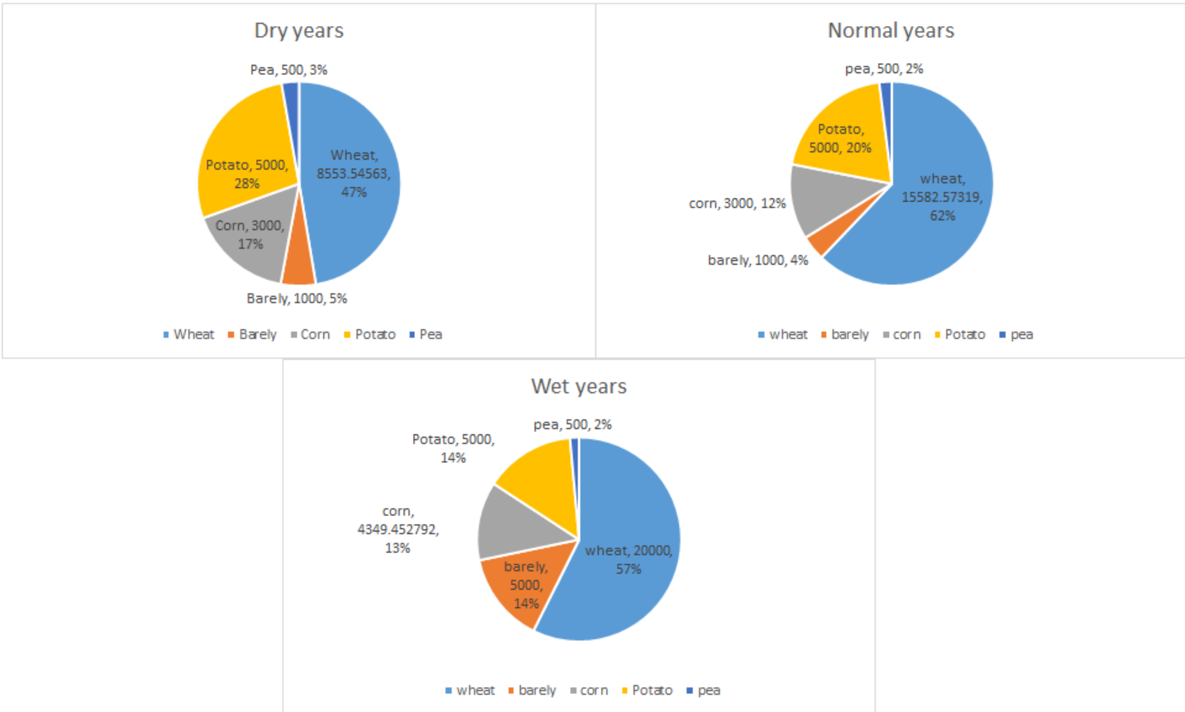



**Figure 8-6-10- Optimal cropping pattern in dry years, normal years and wet years proposed by the optimization system**

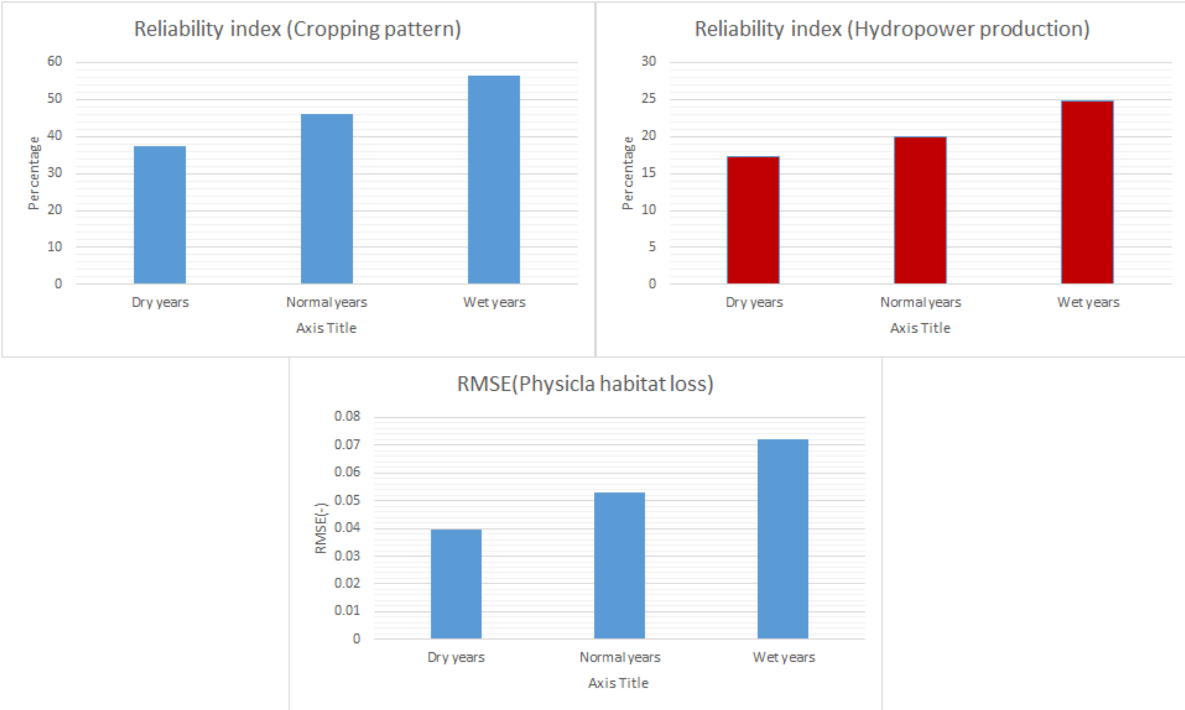



**Figure 8-6-11- Measurement indices for the optimal solutions in the case study**

A full discussion on different aspects of the developed model is essential as well. Each optimization system might have limitations, strengths and drawbacks that should be noted in the applications. Moreover, it is essential to discuss on the future research fields in this regard. We discuss on the developed model based on the technical view and computational view. In this research work, fuzzy physical habitat simulation was utilized as the ecological impact model that demonstrates the robust performance. However, this method might not be useable in all the case studies. For example, absence of robust expert opinions regarding the target species might be a hindrance for using the fuzzy physical habitat simulation in other cases. Other methods might be available in this regard. For instance, the data driven models have been proposed as the robust alterative for the physical habitat simulation in the rivers. Utilizing the artificial neural networks in the simple form or improved form such as adaptive neuro fuzzy inference systems (ANFISs) are recommended in other parts of this thesis. This method is useable when sufficient information is not available regarding the fish species in the study area. However, it might be effective on the efficiency of the optimization model in terms of the computational aspects.

We applied the cropping pattern optimization combined with the reservoir operation optimization to minimize loss of the food and energy production and ecological impact at downstream of the reservoirs. However, other strategies might be useable in the agriculture planning of the lands. For example, deficit irrigation is one of the effective strategies in the agriculture that is able to reduce water consumption.

However, it might decrease the yield of the farms. It seems that using the combined strategies such as coupled deficit irrigation- cropping pattern model could be highlighted in the future studies.

Computational aspects are very effective in the successful application of the optimization systems. Computational complexities might reduce the efficiency of the optimization model drastically. As a definition on this term, it has been defined as the required time and memory to find the optimal solution in the simulated domain. The proposed method is considerably advantageous that means low computational complexities are the most important strength point for the system. It should be noted that importance of the computational complexities might be highlighted in the practical projects. We need to carry out numerous simulations in practice that implies the high computational complexities might be a serious limitation. The engineers are not willing to apply the complex optimization system due to significant limitations such as considerable running time or required memory. As discussed, other types of ecohydraulic simulations such as data driven models of the physical habitat suitability are useable in the proposed method. However, direct using of the data driven model such as ANFIS based models in the structure of the optimization system might increase the computational complexities. Thus, changing the method of the ecohydraulic simulation should be based on computational considerations in the optimization model.

We utilized the PSO as the optimization algorithm in this research work by the single objective function. In fact, we aggregated all the losses in a single objective function. However, using multiobjective algorithms such as MOPSO might be another option as well. In other words, each term of the optimization model could be used as an independent function in the optimization model. However, some disadvantages might confine its applications. First, multiobjective optimization algorithms have the higher computational complexities compared with the single objective algorithms. It might be a serious problem for applying data driven models in the structure of the optimization model. Thus, we proposed an aggregated objective function in which all the terms are available in the objective function. This form of the objective function increases the upgradability of the model for the future studies. Moreover, global optimization is another problem for using a multiovjective algorithm in practice. One of the important weaknesses of the evolutionary algorithms is inability to guarantee the global optimization for the complex objective functions. The proposed method is a complex objective function that might need using different algorithms in the practical projects. However, we used one algorithm as a test of the model. Unfortunately, a limited number of the multiobjective algorithms have been developed in the literature. Thus, using a single objective function is advantageous for using different evolutionary algorithms including classic and new generation algorithms.

One of the recommendations for the future studies is to add the climate change model in the structure of the optimization model. The climate change might affect the inflow of the reservoir drastically that means efficiency of the reservoir in terms of food and energy production and mitigating ecological impact might be changed in the future periods. We recommend utilizing the proposed method in the reservoir operation instead of the available methods that are not able to mitigate loss of the reservoirs in terms of food and energy production and environmental impacts. The conventional form of the reservoir operation optimization is not efficient to overcome the complexities in the river basins. The proposed method provides an upgradeable environment that means other components or improved models could be added to the system.

We selected a particular set of parameters in this research work. It is required to explain the rationale on the choice of the set of parameters in this study. The set of the parameters in this research work was considered based on the technical issues in the reservoir of the case study. In fact, each reservoir might need a specific set of parameters that might not be the same with the other case studies. We did not test other sets of the parameters in this research work. It was not compatible with the technical considerations of the case study, and it is an unrealistic condition that might not be evaluable. However, it is recommendable to apply the proposed framework in other case studies and change the set of parameters based on the needs of the case study. Moreover, some key assumptions were considered in this research work. For example, physical habitat suitability was the main effective parameter on the habitat suitability of the river. This assumption was correct in the case study. Other effective parameters such as water quality were not problematic. However, other case studies might need water quality assessment as well. Moreover, power plants coefficients such as PF were considered as the constant due to recommendations by the regional water authority that was logical in the case study. Furthermore, maximum irrigation demand and maximum revenue were defined based on current cultivation pattern and area in the case study. This assumption helped us to compare the abilities of the optimization model to provide local requirement of the cultivation in the case study. Justifications on other assumptions are explained in the related section.

As a summary of this section, we developed a novel form of the optimization system in which hydropower and food production revenue by the reservoir are maximized while ecological degradations at downstream river is minimized. The fuzzy physical habitat simulation as one of the known ecohydraulic methods was used that is able to simulate physical habitat losses in the river ecosystems. Three purposes were defined in the optimization model including maximizing the hydropower production and food production revenue and mitigating ecological impacts. Three indices were utilized to measure the performance of the optimization system including reliability index of hydropower production, reliability index for farmers' net revenue and RMSE for physical habitat loss. Optimal operation of the reservoir was analyzed in three hydrological conditions including dry years, normal years and wet years. According to the results in the case study, the proposed method is able to optimize reservoir operation in terms of defined purposes in the objective functions. The ecological impact at downstream of the reservoir were minimized perfectly. Moreover, the impact of the hydrological condition on the hydropower production is considerable. The developed method proposed dynamic optimal cropping patterns in dry years, normal years and wet years. We recommend using the proposed method to optimize reservoir operation instead of conventional reservoir operation models in which water supply might be defined as the main purpose of the optimization model.

## 8.7 Summary

This chapter developed several frameworks for considering the environmental flow in the structure of the reservoir operation. In other words, we converted the concept of environmental flow assessment to the environmental flow optimization in which benefits of reservoirs and environmental flow requirements could be simulated and optimized simultaneously. The developed frameworks are advantageous in terms of balancing environmental requirements and potential benefits of reservoirs. A summary of each framework has been presented in the last paragraph of each section.

# Chapter 9: Environmental operation of reservoirs considering combined requirements of water quality and quantity

Full contents of this chapter have been published and copyrighted, as outlined below:

Sedighkia, M., Datta, B., Abdoli, A. and Moradian, Z., 2021. An ecohydraulic-based expert system for optimal management of environmental flow at the downstream of reservoirs. *Journal of Hydroinformatics*, *23*(6), pp.1343-1367.

## 9.1 Introduction

Importance of dams has been highlighted in the literature due to their significant role for development of the communities (Altinbilek, 2002). However, the environmental impacts at the upstream and downstream are undeniable (Wang et.al, 2012). Increasing population might exacerbate the destruction of the river ecosystems due to raising offstream flow in the rivers (Postel, 1998). Due to importance of protecting river ecosystems, different methods have been proposed to mitigate environmental impacts of the hydraulic structures such as dams. Allocating environmental flow regime is an effective solution to protect river ecosystem or aquatic river habitats that might be destructed due to lack of adequate instream flow in the rivers. Many methods have been suggested to assess environmental flow in the rivers (Tharme, 2003). For example, hydrological desktop methods and hydraulic rating methods are the simplest methods to assess environmental flow (Jowett, 1997). However, they are not efficient due to lack of focus on the regional ecological values in the study area (Sedighkia et.al, 2017).

Advanced methods such as instream flow incremental methodology (IFIM) proposed an integrated simulation methodology in which physical and water quality factors have been considered simultaneously (Maddock, 2018). It should be noted that IFIM is a basic framework or process to manage environmental impacts in the river ecosystem. In fact, IFIM provides general methods that should be used to assess environmental flow regime by proposing some phases and mathematical models. Developers encouraged users to consider innovation and creativity in the applications (Stalnaker, 1994). The initial proposed methods by the IFIM are too old that means they might not be efficient to solve the complex environmental problems in the river basins. For example, one of the components of the IFIM is physical habitat simulation. Univariate method has originally been proposed by the IFIM to simulate physical habitats (Ahmadi-Nedushan et.al, 2006). However, this method has been criticized in the literature due to lack of accuracy to simulate interactions between physical parameters including depth, velocity and substrate (Railsback, 2016, Noack et.al, 2013). In fact, this method computes suitability of each parameter and then uses a mathematical index such as geometric mean to compute combined habitat suitability. Using other approaches such as multivariate methods has been highlighted in the literature. One of the applicable and efficient novel methods that might be robust to simulate physical habitats is fuzzy physical habitat simulation. The main advantage of this method is possibility of using expert opinions in the development of the fuzzy physical habitat rules. It seems that response of the fuzzy physical habitat simulation is close to the actual response of the aquatics in the river habitat (Noack et.al, 2013). It should be noted that using knowledge-based models might be very applicable due to complexities of the physical habitat simulation. Water quality simulation is another challenge in the assessment of environmental flow regime. Hydrodynamic models have been developed to simulate water quality factors such as dissolved oxygen or water temperature (e.g Fang et.al, 2008; Sedighkia et.al, 2019). However, these models might not be flexible for applying in the complex water resource management systems. Thus, artificial intelligence methods such as artificial neural network (ANN) have been utilized in the previous studies (Singh et.al, 2009). Due to drawbacks of the ANN such as working as black box, other advanced methods such as adaptive neuro fuzzy inference systems (ANFIS) have been used as well (Tiwari et.al, 2018). ANFIS puts a fuzzy inference system in the structure of the neural network that might increase the interpretability of the prediction system (Jang, 1993).

Reservoirs are one of the complex water resource systems that should be operated optimally due to high cost of the construction of dams. In fact, optimal operation of the reservoirs is critical for maximizing benefits from the reservoir. Linear programming (LP) is a simple method that was used to optimize reservoir operation in previous studies (Reis et.al, 2006). However, it was not able to provide optimal solution for the reservoir operations due to non-linear nature of the problem (Ahmad et.al, 2014). Thus, using non-linear programming (NLP) and dynamic programming (DP) was the next step to improve the optimization methods of the reservoir operation (e.g Arunkumar and Jothiprakash, 2012). Reservoir operation might have a complex objective function. Thus, using advanced computational methods was essential that have been utilized in the literature. Different classic and new generation algorithms have been applied to optimize reservoir operation in the recent years (e.g Afshar et.al, 2007; Afshar et.al, 2011; Ehteram et.al, 2018; Haddad et.al, 2016; Haddad et.al, 2015). Definition of the objective function is another aspect in the reservoir operation problems. Hashimoto et.al, 1982 defined a basic form of the loss function that minimizes the difference between target and release. Target might be defined as the water demand in the reservoir operation system. Datta and Burges, 1984 highlighted adding storage loss in the reservoir operation system. In fact, deviation from the optimal storage might increase storage loss in the system. This form of loss function has been used in many studies even in the recent reservoir operation studies (e.g Ehteram et.al, 2018). However, it seems that this form of loss function is not responsive for overcoming environmental challenges at the downstream of the reservoir. In fact, it is required to develop the novel form of the optimization system that should be able to consider reservoir benefits and complex environmental issues simultaneously. It is required to review recent studies regarding the optimization of the reservoir operation. Predicting the inflow of the reservoir is one of the requirements for management of the reservoirs. Recent studies indicated the applicability of deep leaning methods and improved artificial intelligence methods in this regard (Fu et.al. 2020; Taormina et.al,2015; Shamshirband et.al,2020). Prediction of flood is another important advance in the reservoir managements (Kaya et.al, 2019; Fotovatikhah et.al,2018). Furthermore, reservoir operation has been optimized considering climate change and related uncertainties (Ehteram et.al, 2018).

Simultaneous management of water supply and environmental flow is a complex process. Conventional optimization systems of the reservoir operation are not able to consider the environmental issues in the management of the reservoirs. Hence, improvement of the reservoir operation models considering environmental impacts is essential. Due to complexities of the environmental modeling in the river ecosystems, using expert opinions and optimization system is necessary for improving environmental management of the reservoirs. The main motivation of this research work is lack of robust expert systems in the environmental management of the reservoirs. In fact, this research work proposes an integrated expert system to optimize environmental flow regime at the downstream of the reservoir that might help the water resource managers to overcome the environmental complexities in the reservoir management. The developed model simultaneously mitigates the water supply loss and environmental impacts considering expert opinions. In recent years, ecohydraulics engineering is developed to manage environmental requirements of the river ecosystem in which interactions between abiotic factors such as water quality and quantity with habitat suitability could be utilized for simulating habitats. However, interactions are very complex that means using artificial intelligence (AI) methods could be beneficial. In fact, development of AI methods for modeling environmental challenges is one of the smart solutions that is the main motivation for this research work. Water quality and quantity are separately effective on the suitability of habitats that means integration of them is necessary for managing environmental degradations of the reservoirs. Based on the presented necessities, this research work develops two fuzzy inference systems for assessing water quality suitability and water quantity suitability. Then, these two fuzzy inference systems are integrated with one combined fuzzy inference system to assess combined ecohydraulic suitability. In fact, a knowledge-based system is developed in which fuzzy inference systems were utilized to assess aquatic habitat suitability based on the expert opinions. Then, developed knowledge-based system was applied in the structure of a evolutionary optimization to optimize environmental flow at downstream of the reservoir. In fact, the proposed coupled knowledge based-optimization system can consider environmental issues and reservoir losses simultaneously. This research work might open new windows to apply knowledge-based system in the environmental management in the structure of the water resource operation systems. In fact, each water resource engineering system needs to be managed considering environmental issues. The proposed framework provides an upgradable environment that could demonstrate the high efficiency of knowledge-based system to solve environmental challenges of the water resource systems.

## 9.2 Application and methodology

The proposed method contains three Mamdani fuzzy inference systems including physical habitat suitability assessment system, water quality suitability assessment system and combined suitability assessment system. Moreover, coupled particle swarm optimization- adaptive neuro fuzzy inference system (PSO-ANFIS) data driven model were utilized to simulate water temperature and dissolved oxygen at downstream of the reservoir. Furthermore, different evolutionary algorithms were used to optimize environmental flow. It should be noted that considering fuzzy inference system of combined suitability assessment in which two fuzzy inference systems including physical habitat assessment and water quality assessment are used is advantageous in terms of integrated assessment of the river ecosystem. Other feasible alternatives might be to apply the fuzzy inference system of physical habitat assessment or fuzzy inference system of water quality separately that might not be able to assess integrated environmental suitability. For example, some previous studies only applied fuzzy inference system of physical habitat suitability that is not an efficient method for integrated assessment. Due to complexities of each part of the developed system, full description on different parts of simulation-optimization system is presented in the following sections. Finally, case study is described.

### 9.2.1 Mamdani fuzzy inference system for physical habitat assessment

Two main effective physical parameters were considered in the physical habitat assessment including depth and velocity. A river reach with length of the 10000 meters was considered at downstream of the reservoir. Different cross sections were surveyed in average distance of 100 meters. Then, relationship between depth and discharge as well as velocity and discharge were developed. These developed relationships were utilized in the optimization system to assess depth and velocity in each cross section in each time step. An expert panel was established including an experienced ecologist who was familiar with the regional ecological status of the case study, a water resource engineer and one of the managers of the regional department of environment. A specific method was used to develop fuzzy rules of physical habitats. Figure 9-1 displays workflow of developing fuzzy rules of physical habitats. For example, one of the verbal fuzzy physical rules is displayed as follows. Table 1 displays the main characteristics of the physical habitat fuzzy inference system. Figure 9-2 displays depth and velocity suitability curves used in the case study.

"If depth suitability is medium and velocity suitability is very high, then physical habitat suitability is high"

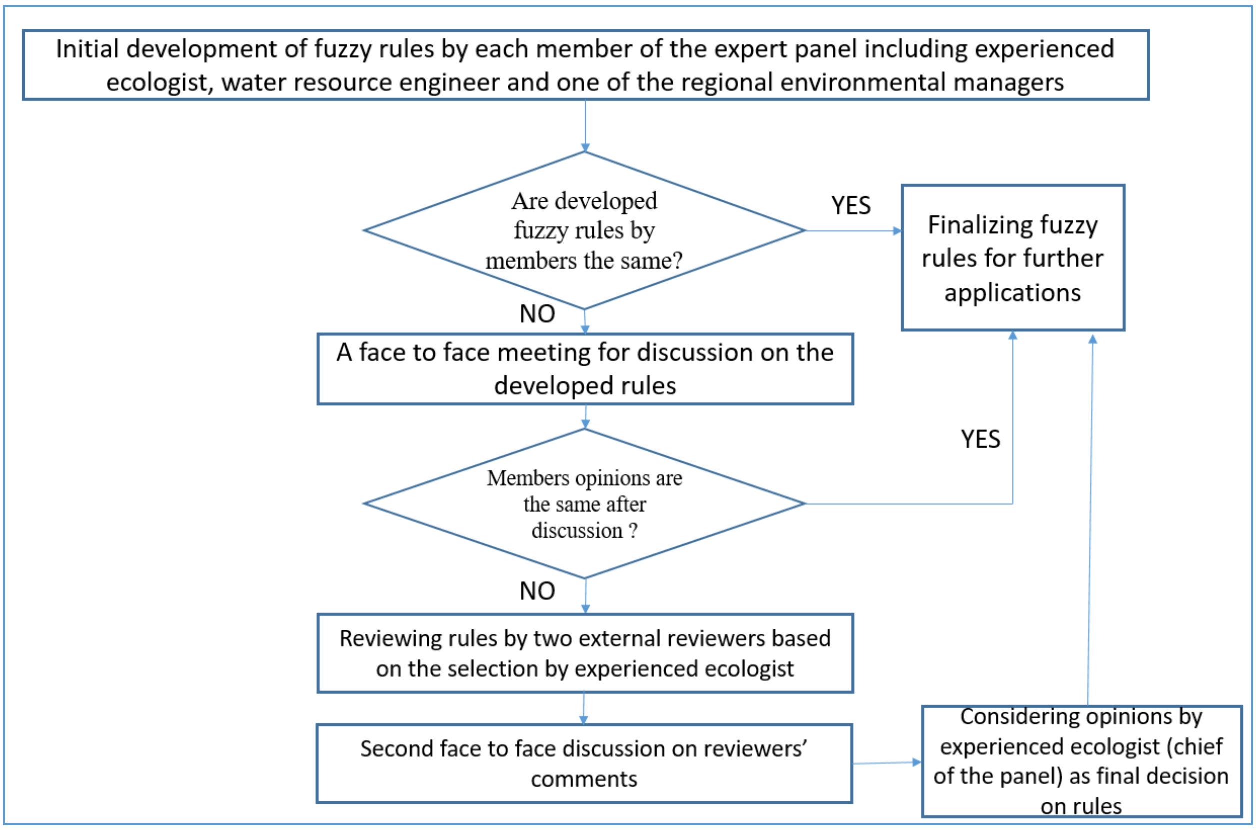



**Figure 9-1-Workflow of the expert panel**

It is essential to present more details regarding the expert panel in the proposed framework. The expert panel includes three members who are familiar with the study area in terms of regional ecological values, management of water resources and regional challenges for environmental management. In fact, the experienced ecologist has extensive information regarding the aquatics needs in the river ecosystem. Moreover, water resources engineer is familiar with the reservoir operation difficulties and needs. Finally, regional environmental manager can address environmental challenges such as negotiations between stakeholders and environmentalist in the panel. At the first glance, it seems that number of experts involved in the panel is not sufficient for making a robust decision. However, it should be noted that each member of the panel might have an independent research team or a group of the colleagues that might be effective on the opinions. In fact, each member can reflect the opinions by a group of experts that sounds enough and logical for a robust expert panel. Another important issue is how conflicting feedback can be handled in the expert panel. As presented in the figure 9-1, two external reviewers who are not the member of the panel would be used to resolve conflicts between the member of the panel. The reviewers' comments will be considered by the chief of the panel (experienced ecologist) to finalize the rules. The proposed panel can develop the robust rules that are significantly effective on the outputs of the optimization system. In fact, this form of the expert panel provides a reliable environment to address scientific and technical issues and regional considerations for developing fuzzy rules.

**Table 9-1- Main characteristics of the knowledge based physical habitat model (fuzzy inference system)**

| Inputs | Number of MFs (inputs) | Type of MFs (inputs) | Outputs | Number of MFs (Output) | Type of MFs (Output) |
|---|---|---|---|---|---|
| **Depth suitability (between zero and one)** | 5 | Triangular | Physical habitat suitability (between zero and one) | 5 | Triangular |
| **Velocity suitability (between zero and one)** | 5 | Triangular | | | |

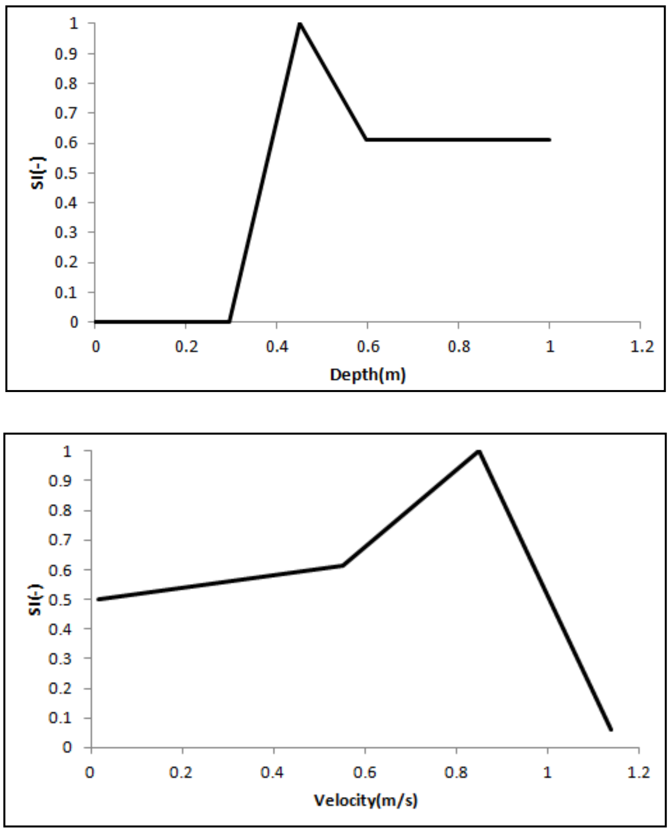



**Figure 9-2-depth and velocity suitability curves**

According to the literature, three main physical factors are effective in the physical habitat suitability including depth, velocity and substrate or bed particle size. However, we only considered two parameters including depth and velocity in this research work due to some reasons. First, effect of depth and velocity is considerably more important on the physical suitability. For example, depth and velocity are effective on the energy consumption by the fish. However, substrate has less effect on the suitability. Moreover, the particle size distribution in the representative reach of the case study was approximately uniform that means the substrate could be excluded in the fuzzy inference system. Generally, three membership functions (MFs) could be utilized in the fuzzy inference systems including triangular, Gaussian and trapezoidal. The previous studies regarding the application of fuzzy inference systems for river habitat suitability corroborate that triangular MFs might provide the proper response. Hence, the triangular membership function was applied in this research work. Using this form of MF makes it possible to compare the developed fuzzy inference system in this research work with previous studies that might be advantageous for the future studies.

### 9.2.2 Mamdani fuzzy inference system for water quality suitability assessment

A fuzzy inference system was developed for the water quality suitability assessment as well. We considered two main water quality factors including water temperature and dissolved oxygen (DO) that might be very effective on the biological activities of the aquatics such as reproduction and searching for food. Other parameters might be important. However, initial assessment in the case study indicated that water temperature and dissolved oxygen could be selected as the key water quality factors. Hence, fuzzy inference system was developed based on these parameters. An expert panel was established to develop fuzzy rules like physical parameters. Following sentence shows one of the examples of the water quality suitability fuzzy rules in this research work. Table 2 displays the main characteristics of the water quality assessment fuzzy inference system. Figure 9-3 shows used biological water temperature and DO models to calculate tension or suitability in the case study.

"If DO suitability is high and water temperature suitability is low, then water quality suitability is medium"

**Table 9-2- Main characteristics of the knowledge-based water quality suitability model (fuzzy inference system)**

| **Inputs** | **Number of MFs (inputs)** | **Type of MFs (inputs)** | **Outputs** | **Number of MFs (Output)** | **Type of MFs (Output)** |
|---|---|---|---|---|---|
| **Dissolved oxygen (DO) suitability (between zero and one)** | 5 | Triangular | Water quality suitability | 5 | Triangular |

| | | | | | |
|---|---|---|---|---|---|
| **Water temperature suitability (between zero and one)** | 5 | Triangular | (between zero and one) | | |

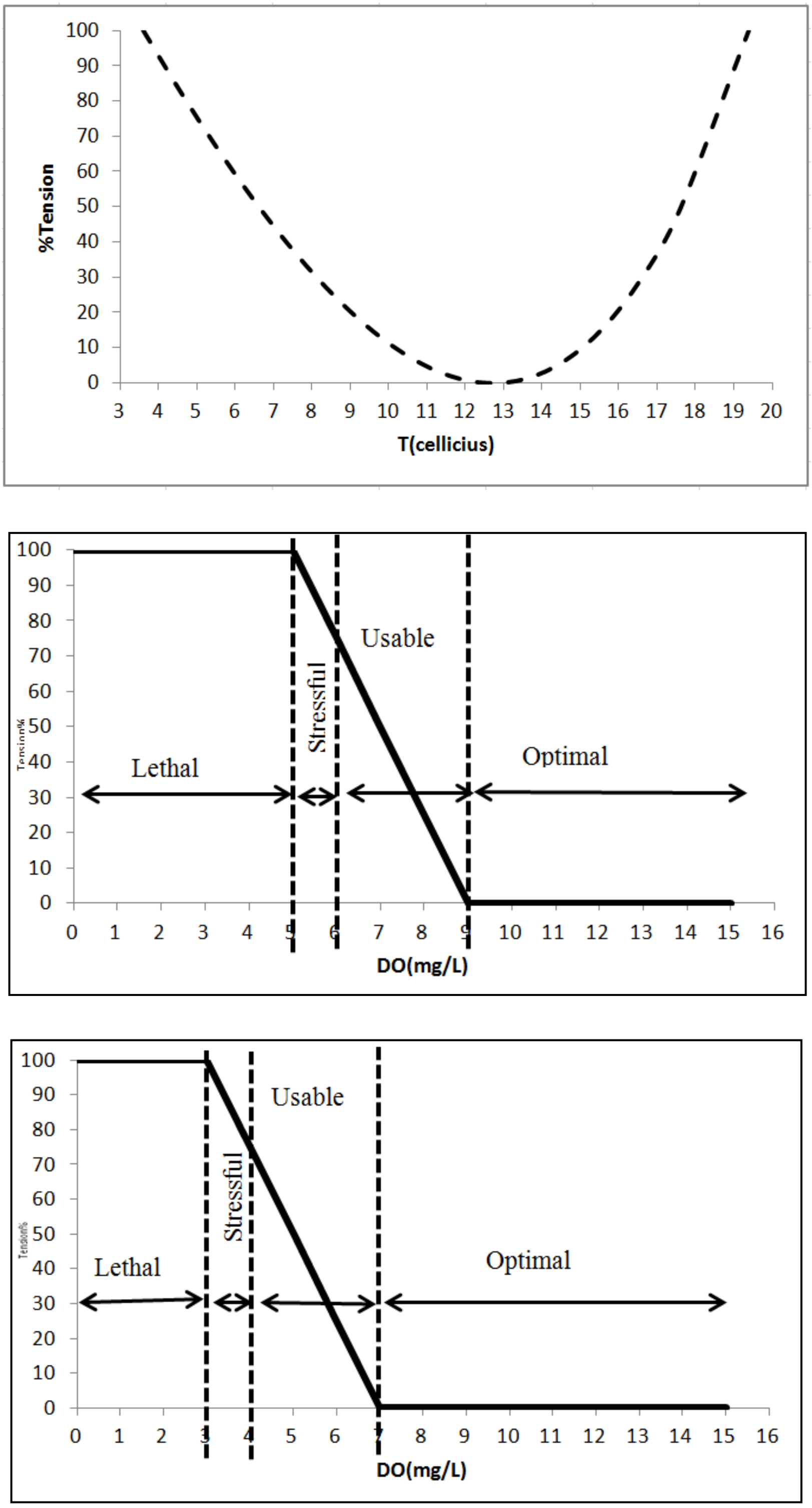



**Figure 9-3-Water temperature and DO biological models (Developed by Sedighkia et.al, 2019)**

Many water quality parameters can be considered in the habitat suitability assessment such as dissolved oxygen, total dissolved solids etc. However, two main water quality parameters that might be effective on the suitability are water temperature and dissolved oxygen. Hence, these two parameters were taken into account in the development of fuzzy inference system. It should be noted that concentration of other constituents might change the water temperature and DO concentration in the water. Thus, these two parameters are proper indices for using in the structure of the fuzzy inference system.

### 9.2.3 Simulation of water temperature and dissolved oxygen (DO)

Simulation of the water temperature and DO might be a complex process. We need a flexible model that could be used in the structure of the optimization model. Thus, ANFIS based data driven model was utilized in this regard due to several advantages. Using evolutionary algorithms might improve training process of the ANFIS based models. Hence, we applied a coupled PSO-ANFIS model to simulate water quality factors in this research work discussed in chapter 5. Table 3 and Table 4 displays main characteristic of the water temperature and DO data driven models respectively. The models were used to simulate these water quality factors in different cross sections of the representative reach that were described in the previous section. Two indices were utilized to measure predictive skills of the data driven model including The Nash–Sutcliffe model efficiency coefficient (NSE) and root means square error (RMSE) as displayed in the following equations.

$$NSE = 1 - \frac{\sum_{t=1}^{T}(OBS_t - SIM_t)^2}{\sum_{t=1}^{T}(OBS_t - OBSm)^2} \qquad (1)$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T}(SIM_t - OBS_t)^2}{T}} \qquad (2)$$

where $OBS_t$ is observed or recorded data in the time step t, $SIM_t$ is the simulated data by the model and T is total number of time steps.

**Table 9-3-Main characteristics of ANFIS based temperature model**

| Inputs | Number of MFs (inputs) | Type of MFs (inputs) | Outputs | Number of MFs (Output) | Type of MFs (Output) | Clustering method |
|---|---|---|---|---|---|---|
| **flow rate ($m^3/s$)** | 10 | Gaussian | Water temperature at each cross section | 10 | Linear | Subtractive Clustering |
| **Wetted perimeter(m)** | 10 | Gaussian | | | | |
| **Distance from the reservoir** | 10 | Gaussian | | | | |
| **Elevation level from the Sea** | 10 | Gaussian | | | | |
| **Water temperature at distance= 0 m ($^o$c)** | 10 | Gaussian | | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| **Air temperature ($^o$c)** | 10 | Gaussian | | | | |

**Table 9-4-Main characteristics of ANFIS based dissolved oxygen model**

| Inputs | Number of MFs (inputs) | Type of MFs (inputs) | Outputs | Number of MFs (Output) | Type of MFs (Output) | Clustering method |
|---|---|---|---|---|---|---|
| **Month (Jan to Dec)** | 10 | Gaussian | DO concentration at each cross section | 10 | Linear | Subtractive Clustering |
| **Rate of flow ($m^3$/s)** | 10 | Gaussian | | | | |
| **Distance from the reservoir** | 10 | Gaussian | | | | |
| **Water temperature at each cross section ($^o$c)** | 10 | Gaussian | | | | |

Many types of data driven models such as neural networks, support vector machine could be applied to simulate water quality in the water bodies. However, the previous studies corroborated the robustness of the adaptive neuro fuzzy inference system (ANFIS) for simulating water quality. Thus, the ANFIS based model was selected in this research work. It should be noted that different methods could be utilized for training ANFIS based models such as back propagation, hybrid and evolutionary algorithms. Recent studies corroborated that using evolutionary algorithms might be a more robust option to train the ANFIS based models. Particle swarm optimization was selected as the best option to train the data driven model. Hence, coupled PSO-ANFIS was applied to generate the data driven models in this research work. Moreover, the previous studies highlighted the effect of several factors on the changing water temperature in the rivers. However, some factors are significantly more effective including considered parameters in the table 3. Using these parameters makes the data driven model simple and robust to simulate water temperature. In fact, selecting these parameters can generate the reliable results while required field measurements are minimized. Similarly, effective parameters were selected for simulating DO concentration in the case study. Furthermore, an explanation is needed regarding the membership functions (MFs). Different types of MFs were tested for developing the ANIFS based model before the main simulation of water temperature and DO concentration for the case study. The initial simulations indicated that Gaussian function is the most robust membership function for simulating water temperature and DO. Hence, this type of MF was selected for the inputs in the ANFIS based models of water temperature and DO.

### 9.2.4 Mamdani fuzzy inference system for combined habitat suitability

This fuzzy inference system was developed to assess combined habitat suitability in which physical habitat suitability and water quality habitat suitability were considered as the inputs of the system and combined habitat suitability is the output of the system. Expert panel-based method was utilized to develop fuzzy rules like previous fuzzy inference systems. Table 5 displays the main characteristic of the developed expert system

**Table 9-5- Main characteristics of the knowledge based combined habitat suitability model (fuzzy inference system)**

| **Inputs** | **Number of MFs (inputs)** | **Type of MFs (inputs)** | **Outputs** | **Number of MFs (Output)** | **Type of MFs (Output)** |
|---|---|---|---|---|---|
| **Physical habitat suitability (between zero and one)** | 5 | Triangular | Combined suitability (between zero and one) | 5 | Triangular |
| **Water quality suitability (between zero and one)** | 5 | Triangular | | | |

## 9.2.5 Optimization system

Development of a correct objective function is the main requirement of each optimization system in engineering. Equation 3 displays the initial form of the developed objective function in this research work. This equation contains two terms including water demand loss and environmental suitability loss. In fact, supply of water demand is the main purpose for construction of many reservoirs. Thus, it should be in the objective function. This term minimizes the difference between target water demand and release for the demand. Moreover, the second term minimizes the difference between combined habitat suitability in the natural flow and the optimal release for environment by the reservoir. It should be noted that considering habitat suitability in the natural flow is a purpose in environmental assessment. In fact, the objective function tries to minimize habitat loss that might be possible due to construction of dam and changing the flow regime in the river. $D_t$ is target water demand, $R_t$ is release for demand, $NCS_t$ is combined suitability in the natural flow and $OCS_t$ is combined suitability in the optimal environmental flow.

$$Minimize\ (OF) = \sum_{t=1}^{T}\left(\frac{D_t - R_t}{D_t}\right)^2 + \left(\frac{NCS_t - OCS_t}{NCS_t}\right)^2 \qquad (3)$$

Each optimization model might need some constraints. In the proposed model, three constraints are required including minimum operational storage in the reservoir, maximum storage in the reservoir and maximum requested water demand from the reservoir. We focused on the using evolutionary optimization in this research work. Thus, it was required to utilize a solution to put the constraints in the structure of the optimization algorithm. Penalty function method is a known method in this regard that has been used in many previous studies (developed by Agarwal and Gupta, 2005). In fact, defined penalty functions increase the penalty of the system when constrains are violated. Three penalty functions were developed as displayed in the following equations. C1 to C3 are constant coefficients that were determined based on the initial sensitivity analysis.

$$if S_i > S_{max} \rightarrow P1 = c1\left(\frac{S_t - S_{max}}{S_{max}}\right)^2 \qquad (4)$$

$$if S_i < S_{min} \rightarrow P2 = c2\left(\frac{S_{min} - S_t}{S_{min}}\right)^2 \qquad (5)$$

$$if\ R_t > D_t \rightarrow P3 = c3\left(\frac{R_t - D_t}{D_t}\right)^2 \qquad (6)$$

Storage in the reservoir should be updated in each time step which is possible by equation 7. Furthermore, overflow could be calculated by the equation 8. $E_t$ is evaporation from the reservoir, $A_t$ is area of the reservoir, $I_t$ is inflow of the reservoir, $ENV_t$ is environmental flow and T is time horizon.

$$S_{t+1} = S_t + I_t - R_t - ENV_t - \left(\frac{E_t \times A_t}{1000}\right), t = 1,2,\dots,T \qquad (7)$$

$$\begin{cases} if\left(S_t + I_t - \left(\frac{E_t \times A_t}{1000}\right)\right) \geq S_{max} \rightarrow F_t = S_t + I_t - \left(\frac{E_t \times A_t}{1000}\right) - S_{max} \\ if\left(S_t + I_t - \left(\frac{E_t \times A_t}{1000}\right)\right) < S_{max} \rightarrow F_t = 0 \end{cases} \qquad (8)$$

### 9.2.6 Optimization algorithms

Different evolutionary algorithms might have different efficiencies in the optimization problems. Thus, using different algorithms might be necessary. Three evolutionary algorithms were utilized in this research work including particle swarm optimization (PSO), differential evolution algorithm (DE) and biogeography based optimization (BBO). Selecting these algorithms was useful to compare performance of algorithms with different origins. PSO is a classic algorithm that has been used in many previous optimization problems successfully (Kennedy and Eberhart, 1995). This algorithm imitates the social behavior of the organism such as the movement of organisms in a bird flock or fish school. DE is non-animal inspired algorithm that is able to indicate the performance of a non-animal inspired algorithm (Qin et.al, 2008). BBO is a new generation algorithm that describes speciation (the evolution of new species), the migration of species (animals, fish, birds, or insects) between islands, and the extinction of species in its mathematical model (Simon, 2008). More details regarding used algorithms have been addressed in the cited documents. Hence, more details have not been presented.

Many evolutionary algorithms have been developed in the literature that might be useable for the optimization problems. However, we selected three algorithms including PSO, DE and BBO based on their originality. PSO is a classic and an animal inspired algorithm that has been utilized in many previous studies. Selecting this algorithm is helpful to investigate the performance of classic algorithms for novel optimization models. Moreover. DE is a known non-animal inspired algorithm that could indicate the performance of the non-animal inspired algorithms compared with animal-inspired algorithms. Furthermore, BBO is a new generation and animal inspired algorithm that was selected to compare outputs of the classic and new generation algorithm in the developed optimization model. Thus, selecting these algorithms among many available evolutionary algorithms is beneficial for comparing outputs of the algorithms in terms of optimization of environmental flow.

### 9.2.7 Measurement indices and decision-making system

Performance of each optimization system should be measured to judge on the outputs. Defining measurement indices should be based on the requirements and the purposes of the developed system. In this research work, three aspects must be considered in the performance measurement including water demand loss, combined suitability loss and storage loss. In fact, loss of water demand and storage are measured to analyze performance of the reservoir in terms of pre-defined purposes of dam construction. Moreover, suitability loss should be measured to assess the performance of the system in terms of design of a proper environmental flow regime. Reliability index was utilized to measure robustness of the system in terms of water demand supply as displayed in the following equation

$$RI_{water\ demand} = \frac{\sum_{t=1}^{T} R_t}{\sum_{t=1}^{T} D_t} \qquad (9)$$

Two indices were used to measure performance of the system in terms of storage loss including vulnerability index and root means square error as displayed in the flowing equations.

$$VI_{storage} = Max_{t=1}^{T}(\frac{S_{optimum} - S_t}{S_{optimum}}) \quad (10)$$

$$RMSE_{Storage} = \sqrt{\frac{\sum_{t=1}^{T}(S_t - S_{Optimum})^2}{T}} \quad (11)$$

Moreover, three indices were applied to measure performance of the system in terms of combined habitat suitability or appropriateness of the designed environmental flow regime. Following equations display used indices. Similarly, these indices were used for measuring physical habitat suitability in the final analysis of the outputs.

$$RMSE_{habitat\ loss} = \sqrt{\frac{\sum_{t=1}^{T}(OCS_t - NCS_t)^2}{T}} \quad (12)$$

$$VI_{habitat\ loss} = Max_{t=1}^{T}(\frac{NCS_t - OCS_t}{NCS_t}) \quad (13)$$

$$NSE_{habitat\ loss} = 1 - \frac{\sum_{t=1}^{T}(ncs_t - ocs_t)^2}{\sum_{t=1}^{T}(ncs_t - ncso)^2} \quad (14)$$

It is required to explain why these indices were selected in this research work to evaluate the simulation-optimization system. The reliability index is one of the basic indices that should be used in the reservoir operation models. More details regarding the importance and role of this index in the reservoir operation optimization have been addressed in the literature. Similarly, vulnerability index is another basic index for measuring the performance of the optimization models of the reservoir operation. More details are available in the cited documents for the reliability index. Moreover, NSE is a robust index for measuring the performance of hydrological models. This index was selected due to its ability for demonstrating how the model can generate the ideal solution for the problem. In fact, NSE provides a transparent picture from the performance of the model compared with the ideal solution. Furthermore, RMSE is a robust statistical index to compare the ideal solution and optimal or simulated solution that has been applied in many previous studies. Selecting these familiar and known indices in the literature makes the output of the case study comparable with other case studies that might be helpful to develop a robust optimization system in practice. FTOPSIS was applied to select the best algorithm. More details are available in chapter 8

### 9.2.8 Case study

Jajrood river is one of the important rivers in the Ghom lake basin in Iran where is habitat for several native fish species. Moreover, this river is responsible for supply of part drinking water demand of the capital territory in Iran. Latian dam has been constructed at the midstream of this river to regulate water supply. Department of environment is concerned regarding protection of aquatics habitats at downstream of this reservoir due to lack of sufficient release to downstream. On the other hand, regional water authority is concerned regarding loss of the water supply and storage due to considerable release for environment. Owing to importance of protecting the river habitats and minimizing loss of the reservoir, using a simulation-optimization system that is able to optimize operation of the reservoir in terms of water supply and environmental considerations is necessary. In fact, the simulation-optimization system should be able to minimize habitat loss and reservoir losses simultaneously. Utilizing a knowledge- based system might be the best option due to complexities of habitat selection in the river habitats. The Brown trout was selected as the target species based on the opinion by the experienced ecologist who was familiar with ecological zones in the river basin. Figure 9-4 displays river network and elevations at the upstream catchment of the Latian dam and location of the reservoir. A 12 months period was selected as the simulation period. From technical view, Jarood River was the good option as the case study. In fact, we selected the Jajrood River as the case study due to the following reasons

1-The extensive ecological field studies had been carried out in this river that means adequate ecological information for development of the habitat suitability fuzzy inference systems were available. It should be noted that the availability of the previous ecological studies in the river ecosystem is prerequisite for using the proposed method in each case study.

2-Environmental management is a challenging issue in this river due to considerable water demand and valuable habitats. Hence, using the proposed method in the Jajrood River can demonstrate the abilities of the proposed method for managing environmental challenges of the reservoirs.

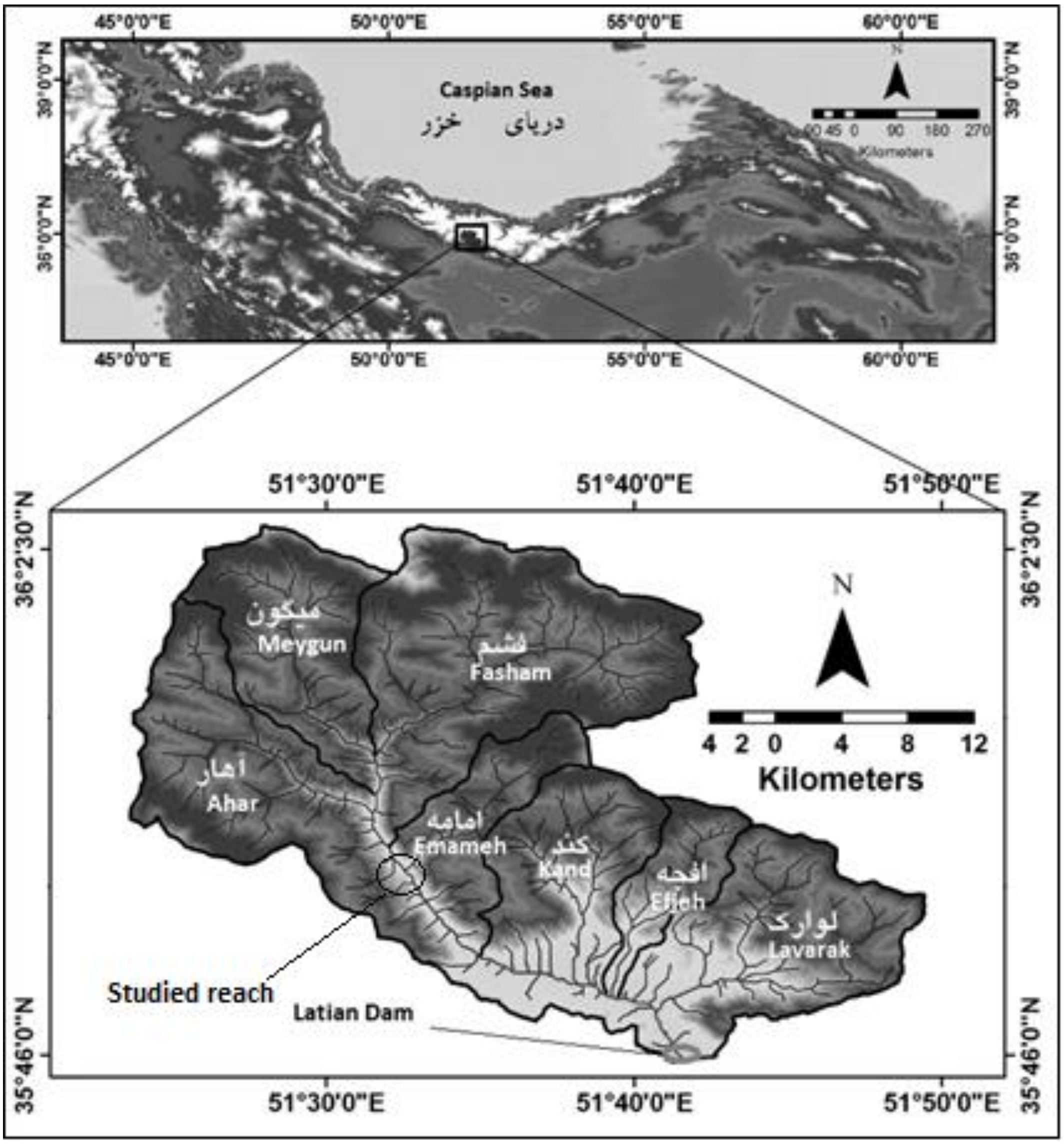



**Figure 9-4- Location of study area at upstream of Jajrood river basin**

## 9.3 Results and Discussion

In the first step, it is required to present and discuss on the results of the ANFIS based model of the water temperature and DO. Figures 9-5 and 9-6 display results of the training and testing process of the water temperature and DO model respectively. Computed NSE and RMSE are shown on the figures. NSE for water temperature model is 0.81 that demonstrates model is very robust to simulate water temperature of the stream. According to the literature, if NSE is more than 0.5, predictive skills of the model will be very robust. Moreover, RMSE is 1.06 that demonstrates mean error of the model to simulate water temperature is negligible for applying in the environmental studies.NSE for the DO model is 0.77. Thus, DO model is reliable and robust as well. Low mean error of the DO model corroborates the reliability of the model to simulate dissolved oxygen in the further steps.

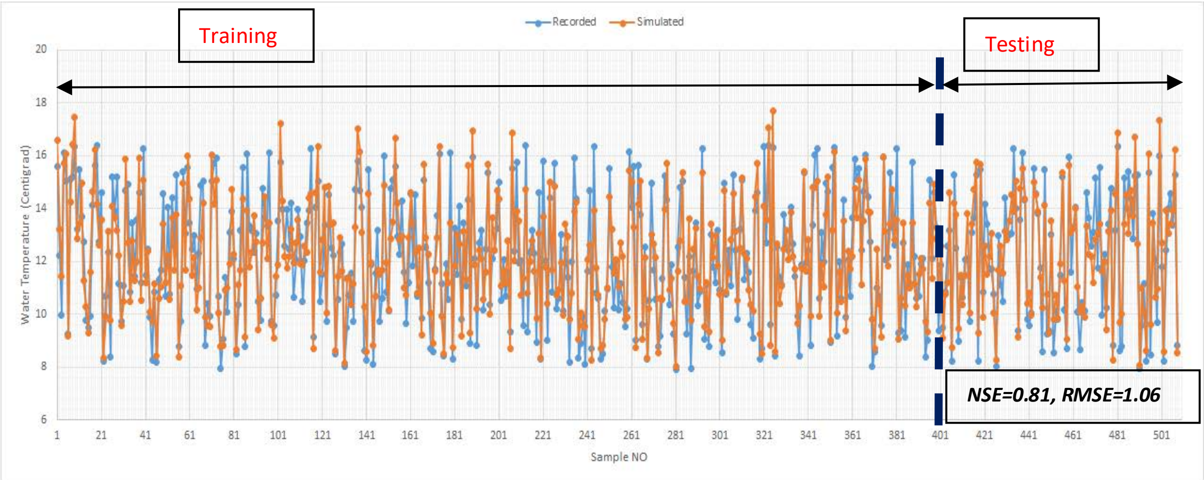



**Figure 9-5- Training and testing process of the stream temperature model**

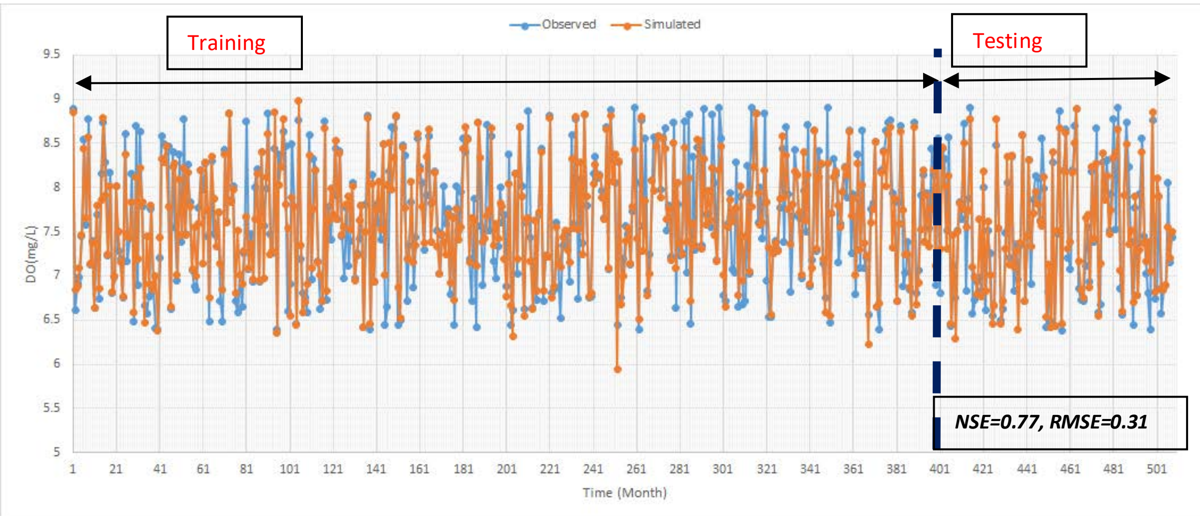



**Figure 9-6- Training and testing process of the DO model**

Tables 6 to 8 display developed fuzzy inference systems or knowledge based systems for assessment of physical habitat suitability, water quality suitability and combined suitability. It seems that the role of velocity suitability is significant. In fact, reducing velocity suitability might decrease physical habitat suitability considerably. Depth suitability is important as well. However, velocity might be more important in the physical habitat suitability. The main reason for the significant role of velocity suitability is alteration of energy consumption by fish due to changing flow velocity. In fact, fishes should swim to the upstream of the river for main biological activities such as reproduction. Thus, increasing flow velocity would rise needed energy for swimming to the upstream that might reduce physical suitability. Developed physical fuzzy rules were utilized in the optimization model directly.

Table 7 displays fuzzy rules for the water quality suitability in which DO suitability and water temperature suitability were considered as the inputs of the system. It seems that importance of the DO suitability is considerable. It should be noted that the target species is such sensitive to DO suitability. Hence, significant role of DO in the water quality suitability is clear based on the developed fuzzy rules. It sounds that water temperature suitability in combination of the DO suitability might be very effective to reduce suitability when DO suitability is medium to high. In fact, the role of water temperature and depth in the knowledge based systems are similar. The developed rules indicate that expert panel should be familiar with the role of parameters to assess biological response of aquatics in the study area. It sounds that selected procedure in the development of knowledge based rules is correct. In fact, experienced ecologist should make final decision on the rules. However, opinions by other experts would be considered in the discussions when there are significant discrepancies. Table 8 displays combined suitability fuzzy rules that shows similar role of physical habitat suitability and water quality suitability in this knowledge based system. The rule code was used in the meetings of the expert panel for being concise in the discussions. For example, if one of the members was not satisfied with one of the rules, he/she only declares the rule code for shortening the discussions.

**Table 9-6- Parts of fuzzy rules for knowledge based physical habitat model (VL means very low, L means low, M means medium, H means high and VH means very high)- total number of rules is 25**

| Rule Code | Depth suitability | Velocity suitability | Physical habitat suitability |
|---|---|---|---|
| **P1** | *VL* | *VL* | *VL* |
| **P2** | *VL* | *L* | *VL* |
| **P3** | *VL* | *M* | *L* |
| **P4** | *VL* | *H* | *M* |
| **P5** | *VL* | *VH* | *M* |

**Table 9-7- Parts of fuzzy rules for knowledge based water quality suitability model (VL means very low, L means low, M means medium, H means high and VH means very high) - total number of rules is 25**

| Rule Code | DO suitability | Water temperature suitability | Water quality suitability |
|---|---|---|---|
| **Q1** | *VL* | *VL* | *VL* |

| | | | |
|---|---|---|---|
| **Q2** | *VL* | *L* | *VL* |
| **Q3** | *VL* | *M* | *VL* |
| **Q4** | *VL* | *H* | *VL* |
| **Q5** | *VL* | *VH* | *VL* |

**Table 9-8- Parts of fuzzy rules for knowledge based combined suitability model (VL means very low, L means low, M means medium, H means high and VH means very high) - total number of rules is 25**

| Rule Code | Water quality suitability | Physical habitat suitability | Combined habitat suitability |
|---|---|---|---|
| **C1** | *VL* | *VL* | *VL* |
| **C2** | *VL* | *L* | *VL* |
| **C3** | *VL* | *M* | *VL* |
| **C4** | *VL* | *H* | *VL* |
| **C5** | *VL* | *VH* | *VL* |

In the next step, output of the optimization system as the main results of the proposed framework are presented and discussed. Figure 9-7 displays the proposed environmental flow by the optimization system in which results of three used algorithms are shown. Performance of different algorithms is not similar. In fact, assessed environmental flow regimes indicate the importance of using different algorithms in the optimization system. Utilizing one algorithm might generate unreliable results. Whereas, using different algorithms makes it possible to select the best outputs of the optimization system. It should be noted that applying more algorithms might be better option. However, it is time consuming. Hence, selecting algorithms should be based on technical considerations similar to this research work. Three to four algorithms with different origins might be a good option in the practical projects.

Figure 9-8 displays supplied water demand by different algorithms. It should be noted that maximum water demand was considered 13 m3/s in all time steps. It seems that either PSO or BBO releases more water for demand compared with DE. Thus, these algorithms might be robust in term of water demand supply in the case study. However, better judgment needs using reliability index. Figure 9-9 displays storage time series in the simulated period for three algorithms. Performance of penalty functions including maximum storage and minimum operational storage are robust. However, owing to simulating a challenging period, storage in the reservoir is not close to maximum storage. Thus, performance of the minimum storage functions is better criterion to judge on the performance of optimization model in terms of storage penalty function. Minimum operation storage is 19 MCM. All algorithms optimized storage in the reservoir considering this minimum value. However, performance of PSO is slightly weaker than others.

It is required to investigate performance of the optimization system in term of designing environmental flow. Optimized physical habitat suitability, water quality suitability and combined habitat suitability should be compared with these values in the natural flow. Figure 9-10 displays physical habitat suitability by different algorithms in the optimal release for environment and the natural flow. Better performance of DE compared with other algorithms in terms of physical habitat suitability is clear. It is able to minimize the difference between optimal physical habitat suitability and the physical habitat suitability for the natural flow. Moreover, performance of BBO is better than PSO in terms of physical habitat loss.

Water quality suitability for different algorithms indicates that optimization model is robust in this regard (Figure 9-11). Performance of the three used algorithms is very good that means they are able to minimize the difference between suitability of optimal release for environment and natural flow. Thus, optimization model is able to reduce environmental advocators' concerns regarding water quality. It should be noted that unsuitable concentration of dissolved oxygen and water temperature might be a primary reason for perishing sensitive aquatics such as the Brown trout. In fact, DO and water temperature have remarkable impact on the biological activities of the Brown trout. The previous biological studies in the tanks demonstrated that unsuitable water temperature raises the biological tensions for the Brown trout quickly. In other words, all the biological activities such as searching for food and reproduction can be stopped in the unsuitable water temperature that means survival of the fish might be threatened. Furthermore, the previous studies corroborate that high concentration of DO is a vital requirement for the Brown trout that means low concentration of DO is considerably detrimental for the survival of the Brown trout.

Figure 9-12 displays combined habitat suitability which is result of using knowledge based combined habitat suitability system in the structure of the reservoir operation optimization. In previous parts, some qualitative judgments on the results were possible observably. However, judgment on the algorithms in terms of combined habitat suitability might not be possible observably. Generally, qualitative judgment on the environmental parameters might not be applicable to use in the robust decision-making system. Hence, using qualitative assessments for making final decisions is not recommendable in the practical project of the environmental flow assessment. Measurement indices are very helpful in this regard to make a right decision for final design of environmental flow regime.

Figure 9-13 displays measurement indices for reservoir losses including reliability index for water supply, vulnerability index and RMSE for storage loss. Moreover, Figure 9-14 displays measurement indices for combined habitat loss. PSO is the best algorithm in terms of water supply. In fact, it is able to supply 60% of requested demand for the reservoir. DE has the lowest reliability for water demand based on outputs of the optimization system. Performance of optimization system in terms of storage loss might be more complex. PSO has the highest vulnerability index. However, it does not have the highest RMSE. In other words, performance of the PSO in one of the time steps is very weak that might generate the highest vulnerability. Whereas mean error of the DE is higher than PSO. Performance of the BBO is between these two algorithms.

The main purpose of the proposed framework is to develop a robust knowledge based system to optimize environmental flow at downstream of the reservoirs. Hence, evaluation of the performance of the optimization system in terms of environmental aspects including physical, water quality and combined suitability might be the most important part in the discussion on the results. Some point should be noted before discussion on the result of the measurement indices for environmental aspects. First, it might be logic to discuss on the results only by using measurement indices for combined habitat suitability. It shows final output of the system. However, we computed measurement indices for physical habitat suitability as well to increase reliability of the analysis. Secondly, it should be noted that performance of the optimization system in terms of water quality suitability was very robust that could be judged observably. Thus, we did not consider measurement indices for the water quality suitability in the discussion and decision-making system separately.

Figure 9-15 displays computed measurement indices for the physical habitat suitability in which vulnerability index, RMSE and NSE have been applied. Each index is helpful to measure one of the aspects in the analysis of the results. Vulnerability index indicates how optimization system might harm the river habitats in the worst time step. Moreover, RMSE might show mean error in the simulated period compared with natural flow. The best status of the river is the natural flow. Hence, using NSE could be helpful to demonstrate how optimization model is able to simulate suitability of natural flow in the optimal release for environment. Vulnerability index for all algorithms is close that indicates none of algorithm is very robust because the vulnerability index is close to 70% that might be a serious concern. The vulnerability index indicates the maximum difference between natural suitability and optimal suitability in the simulated period. When the vulnerability index is 70%, the optimal suitability is considerably lower than natural suitability in some timesteps that might be a serious threat for providing a suitable environment for the aquatics in the river. However, it should be noted that simultaneous management of the environment and water demand might be challenging in the river ecosystem and some threats are inevitable. Owing to simulation of a challenging period of the reservoir operation, this output might not be surprising. Supply of water demands, storage requirements and environmental demands might not be possible perfectly. High RMSEs for all algorithms corroborate the weakness of the optimization system in terms of physical habitat suitability due to low inflow to the reservoir. However, performance of DE is better than other algorithms. NSEs demonstrate that optimization model is not able to provide physical suitability close to the natural flow. NSEs for three algorithms is less than zero that might show the weaknesses of the system in the case study. It should be noted that it is not the weakness of the developed knowledge based method. In fact, it is as result of the low inflow to the reservoir. The results of the case study demonstrate that assessment and management of the environmental flow might be very complex in challenging period. Thus, Not only would using a robust knowledge based system be a good suggestion, but it is also a requirement for assessment and management of the environmental flow at downstream of the reservoirs in many cases.

Vulnerability index for the combined habitat suitability is much less than physical habitat suitability that demonstrates some key points. First, the optimization system prioritized to reduce the combined unsuitability in the objective function considering less water quality unsuitability. In other words, we face a complex situation in the river ecosystems that might be analysed from different views. RMSEs and NSEs indicate that optimization model is able to provide sufficient combined suitability for downstream river ecosystem compared with the natural flow. To sum up, performance of the optimization model is generally acceptable. It is able to increase combined suitability dramatically. However, its performance in term of physical habitat suitability is not perfect. Table 9-9 displays rating of alternatives for applying FTOPSIS method. Figure 9-16 displays the final ranking of the methods by the FTOPSIS method. DE is the best candidate to optimize environmental flow in the proposed method.

One of the questions that should be answered is how the input parameters of the model were selected in this research work. It should be noted that the particular set of parameters for each model was selected based on the previous studies. For example, the previous studies corroborate that depth and velocity are the most important parameters that are effective on the physical habitat suitability of the river habitats that was the main reasons for selecting these parameters in the physical habitat model. Moreover, sensitivity analysis of effective parameters on the water temperature by the previous studies demonstrated that selected parameters are the most sensitive parameters for changing water temperature in the streams. To sum up, the parameters were selected based on many previous studies on the river habitats that determined sensitive parameters for simulating habitat suitability in the rivers.

More discussion on the technical aspects and details of the developed model is essential. The proposed method considered the physical habitat suitability and water quality suitability as the most important factors in the river habitats in an integrated framework that is the main advantage of the proposed method. Flow velocity and depth are effective on the energy consumption by the fish that means considering these two parameters is necessary in each habitat suitability assessment of the aquatics. Depth might be important for sheltering the fishes in the habitats as well. It seems that suitable management of velocity and depth is able to provide the minimum requirements for protecting aquatic habitats in terms of physical factors. Moreover, water temperature and concentration of DO are key water quality factors that might be effective on the suitability of river habitats. Other parameters could be added to the system as well. However, the proposed water quality parameters in this chapter are the key parameters in the aquatic habitats. It should be noted that changing the concentration of other constituents such as total dissolved solids or total suspended solids might change the water temperature and concentration of DO in the water bodies. Hence, it is recommendable to apply water temperature and concentration of DO as the critical water quality parameters for modelling suitability of river habitats. Furthermore, adding climate change models to the proposed expert system is recommendable for the future studies. In fact, climate change might alter the stream flow or inflow of the reservoir that is significantly effective on the management of environmental flow in the reservoirs. It should be highlighted the abiotic parameters were considered in this research work. It is recommendable to add the biotic factors such as predation in the future research works.

Each method or system might have some advantages and disadvantages that should be noticed for the practical projects. In fact, discussion on the strength and limitation of the proposed method is essential. Moreover, it should be discussed why the proposed mechanism was prosperous in the case study to assess the environmental flow regime. Using a knowledge based system is useful in the assessment of environmental flow. We face a complex ecological status in the rivers that might not be measurable in many aspects. However, experts might have strong view on the complexities of the system that is based on many qualitative observations and study on the ecological aspects of the case study. These experts' opinions might not be useable without development of a robust knowledge based system. Moreover, water resource systems such as reservoirs are complex. They should be able to supply different needs including humans' needs and environmental needs. Thus, using optimization models in the management of the water resource systems is necessary. The proposed method puts a knowledge based environmental model in the structure of an optimization system that might be the most important point to propose appropriate environmental flow regime. This system was able to provide requirements of the reservoir management simultaneously. Hence, we can claim that the proposed method is an integrated method to assess environmental flow regime. Another advantage of the proposed model is upgradability. In other words, other effective factors could be added to the system in future studies. It should be noted that fishes are not the main species for all of the rivers. Hence, using other target species might be another option in the assessment of the environmental flow regime. The proposed method is upgradable in this regard. The main limitation of the proposed method is high computational complexities. This term can be defined as the required time and memory to the optimization model to find the best solution. Practical projects might need many simulations or covering a long-term period. The proposed method needs much time for running due to using several fuzzy inference systems in the structure of the evolutionary algorithm. Furthermore, simultaneous simulations might need considerable memory that might be a concern for successful application of the proposed method in the practical projects. We recommend focusing on the reduction of computational complexities in the future studies that increases applicability of this method.

Moreover, some key points should be discussed regarding the optimization model. First, why three different evolutionary algorithms have been applied in this research work. Secondly, why the single objective evolutionary algorithms have been utilized to optimize reservoir operation. Thirdly, more details regarding the application of the evolutionary algorithms in this research work. The main drawback of the evolutionary algorithms is inability to guarantee the global optimization that means using one evolutionary algorithm might not be reliable to find the best solution. Thus, utilizing different evolutionary algorithms and a robust decisions-making system are a requirement for the complex optimization system such as developed model in this research work. It should be noted that there is serious concern for guaranteeing the global optimization by the evolutionary algorithms particularly in the complex objective functions. Furthermore, it is observable that the proposed objective function contains different terms that might be useable in the structure of the multi-objective optimization algorithms. However, two points convinced the researchers of this research work to apply single objective algorithms instead of multi-objective algorithms. First, the proposed method in the single objective form has high computational complexities that is a limitation for the system. Multi-objective optimization algorithms such as multi-objective particle swarm optimization (MOPSO) inherently have higher computational complexities compared with single objective optimization algorithms. Hence, using the multi-objective algorithms might make the optimization model very complex. In other words, required time and memory will be very high for implementing the model in the projects that might reduce the applicability of the model for the engineers. Secondly, the limited number of multi-objective algorithms have been developed in the literature that means applying these algorithms might not be reliable enough in terms of global optimization in the current condition. However, many single objective algorithms have been developed in the literature with different origins that might help the researchers to find the best solution using a robust decisions-making system such as FTOPSIS. In this research work, number of iterations were considered as the stop criterion for the evolutionary algorithms. In other words, high number of iterations (i.e 10000) was considered for the optimization algorithms to find the best solution. This number of iterations was reliable as the stop criterion in the optimization model. In fact, the best solution was found by the algorithms when the number of iterations was 5000 that means the selected criterion was reliable.

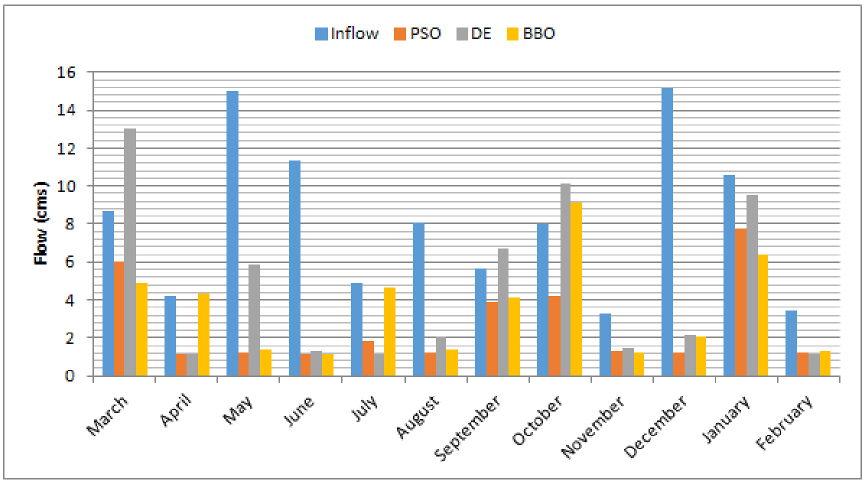



**Figure 9-7- Assessed environmental flow regime by different algorithms**

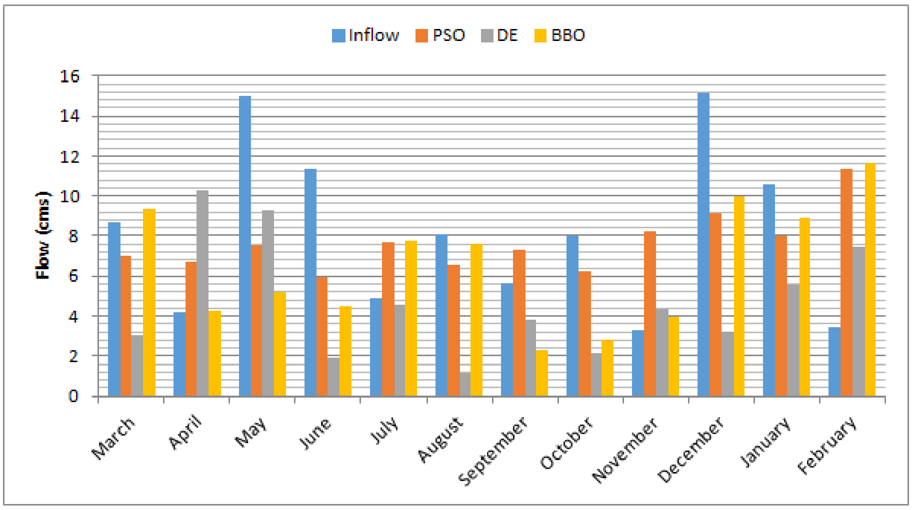



**Figure 9-8- Release for water demand by different algorithms**

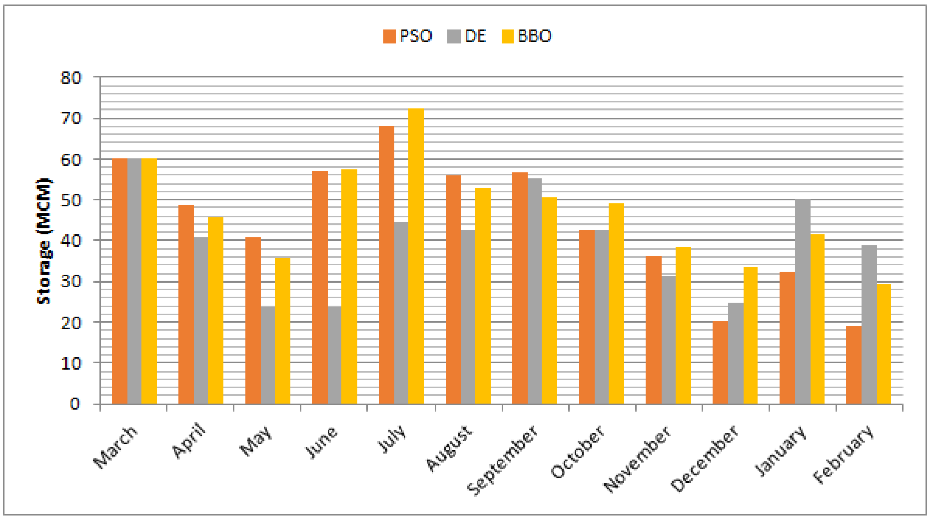



**Figure 9-9- Storage time series by different algorithms**

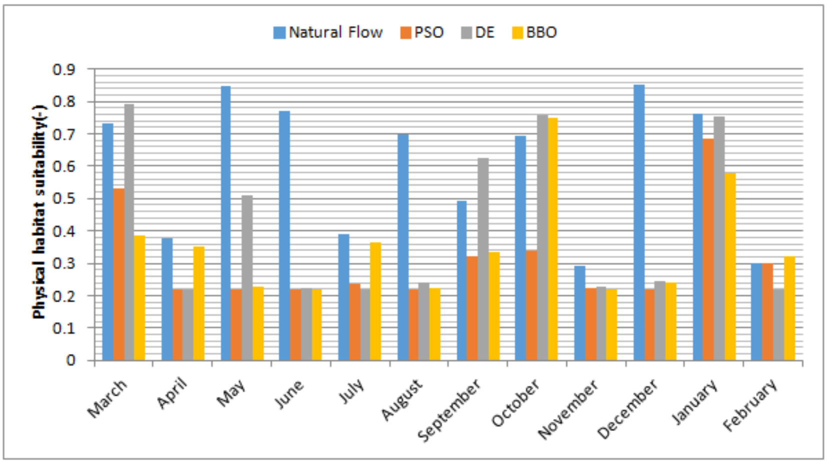



**Figure 9-10- Physical habitat suitability by different algorithms**

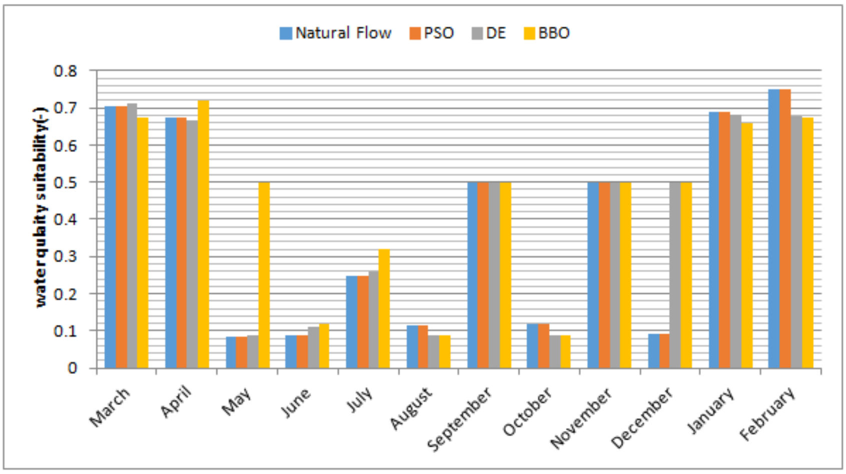


**Figure 9-11- Water quality suitability by different algorithms**

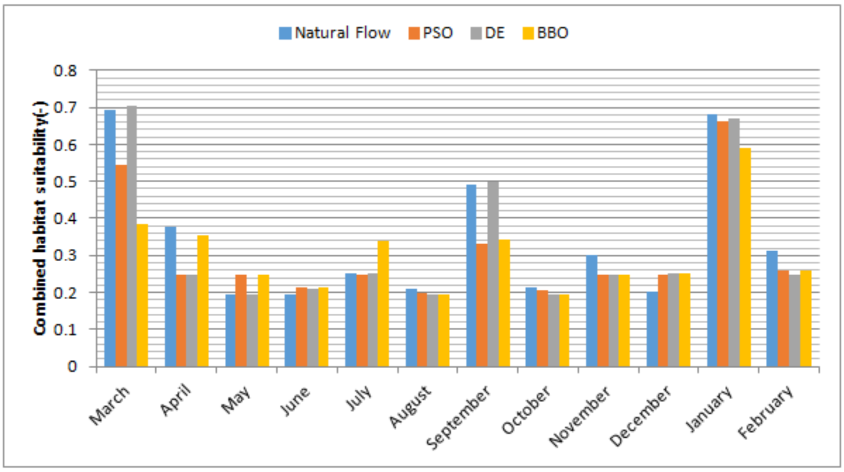



**Figure 9-12- Combined suitability by different algorithms**

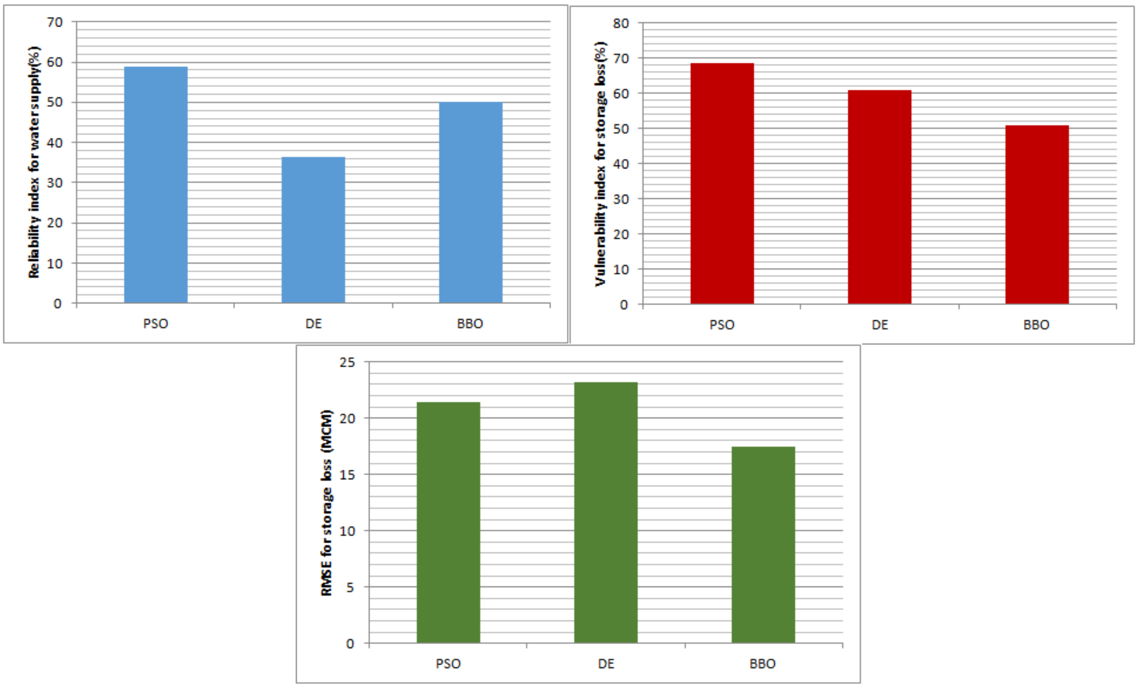



**Figure 9-13- Measurement indices for water demand loss and storage loss**

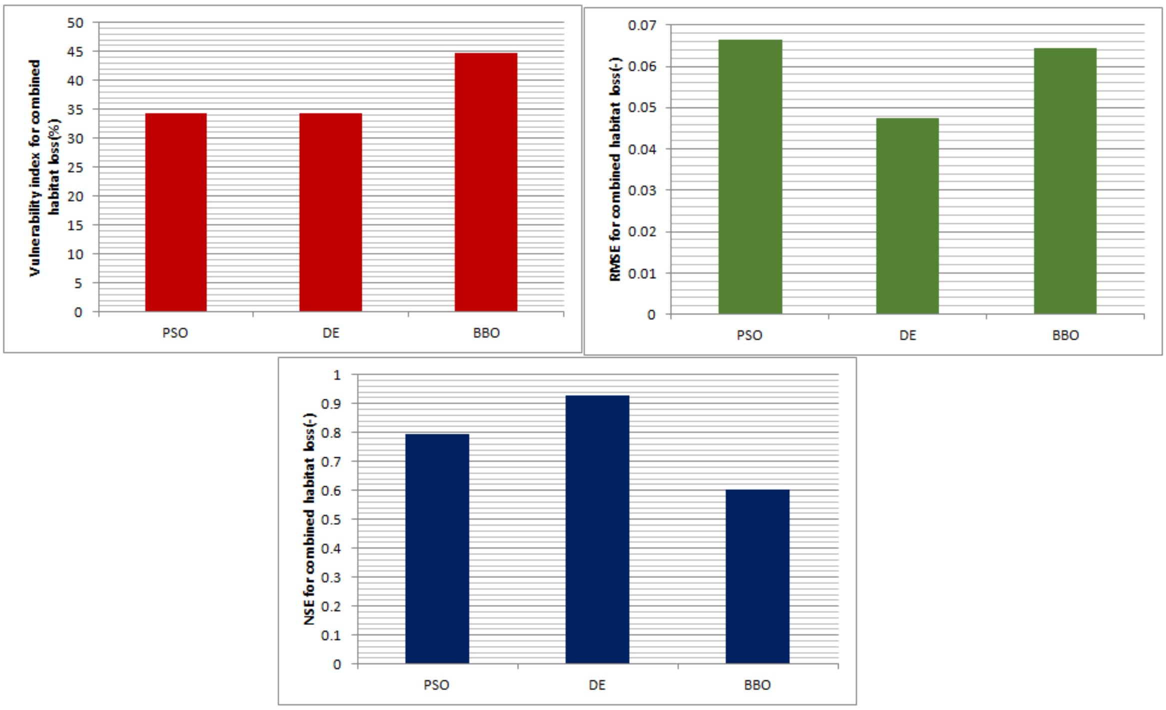



**Figure 9-14- Measurement indices for combined habitat loss**

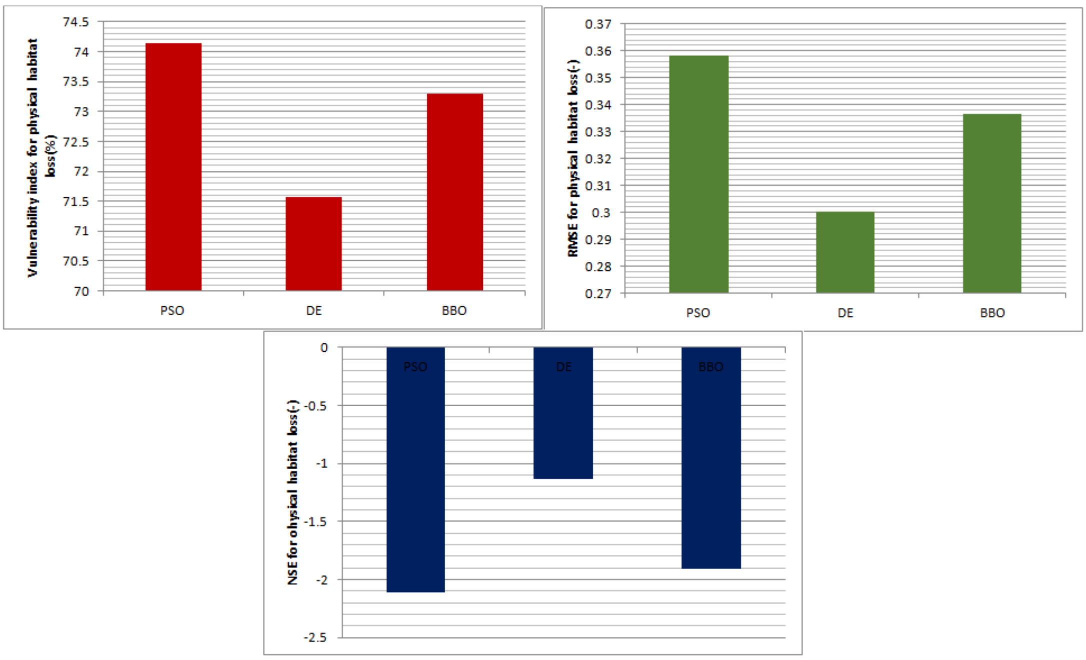



**Figure 9-15- Measurement indices for physical habitat loss**

**Table 9-9- Sample of rating of alternatives for some selected indices (based on method by Chen, 2000)**

| | PSO | DE | BBO |
|---|---|---|---|
| RI(water supply) | *G* | *RG* | *RP* |
| VI (Storage) | *VG* | *G* | *RG* |
| RMSE (Storage) | *G* | *G* | *RG* |
| VI (Combined suitability) | *G* | *G* | *VG* |

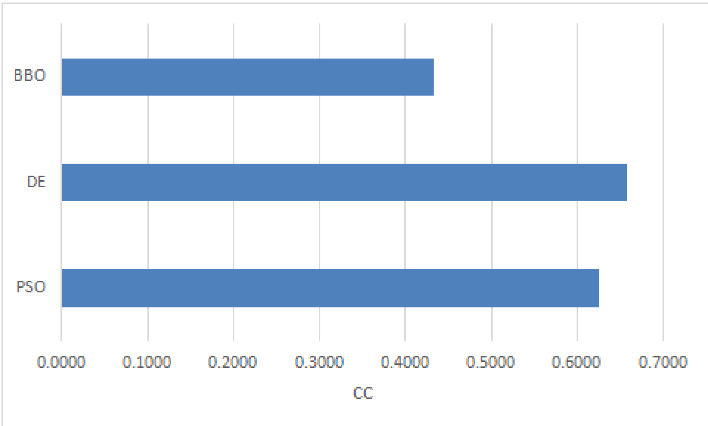



**Figure 9-16- Final ranking by the FTOPSIS method**

## 9.4 Summary

Linking ecohydraulic modelling and reservoir operation optimization is a requirement for robust management of the environmental degradations at downstream of the reservoirs. This research work proposes and evaluates an ecohydraulic based expert system to optimize environmental flow at downstream of the reservoirs. Three fuzzy inference systems including physical habitat assessment, water quality assessment and combined suitability assessment were developed based on the expert panel method. Moreover, water temperature and dissolved oxygen were simulated by the coupled particle swarm optimization-adaptive neuro fuzzy inference system. Three evolutionary algorithms including particle swarm optimization (PSO), differential evolution algorithm (DE) and biogeography-based optimization (BBO) were applied to optimize environmental flow regime. A fuzzy technique for order of preference by similarity to ideal solution was applied to select the best evolutionary algorithm to assess environmental flow. Based on the results in the case study, the proposed method provides a robust framework for simultaneous management of environmental flow and water supply. DE was selected as the best algorithm to optimize environmental flow. The optimization system was able to balance habitat losses, storage loss and water supply loss that might reduce negotiations between the stakeholders and environmental managers in the reservoir management.

# Chapter 10: Conclusions and recommendations

## 10.1 Conclusions

This thesis highlighted the optimal dam/reservoir operation emphasizing environmental challenges and possible impacts by the climate change. Several applicable frameworks were developed in which different aspects of downstream environmental impacts were integrated with the optimal operation of a dam/reservoir. Outputs of each framework have been discussed in the respective chapters. Moreover, a summary has been presented at the end of each chapter. This chapter outlines some key points as the conclusions of the thesis. Furthermore, this chapter presents some important recommendations for using the proposed methods and future research needs.

The following conclusions should be noted:

*Conventional reservoir operation models in which economic losses of the operation have been highlighted are not able to integrate the environmental requirements in the optimal operation of a reservoir or a diversion dam. In other words, developing and using environmental operation is important to mitigate downstream environmental impact.

*Increased water demand in recent decades can exacerbate the downstream environmental impacts, which means using environmental operation of the hydraulic structures is vital for sustainable development in all river basins.

*Climate change may worsen the environmental impact of water or hydropower supply, which means integrating climate change models in an operation optimization framework, is essential for overcoming potential challenges.

*Previous studies developed some initial frameworks for integrating environmental modelling in dam/reservoir operation. However, advanced environmental models such as habitat-based models of environmental flow have not been applied in most previous studies of dam/reservoir management. This thesis integrated the advanced methods of environmental modelling such as habitat simulation in the operation optimization, which might be advantageous to project environmental requirements

*The proposed methods are able to deescalate negotiations between stakeholders and environmental managers due to balancing environmental requirements and benefits of a diversion dam or reservoir.

*Not only physical habitat requirements have been considered for assessing downstream environmental impacts, also, water quality impacts have been simultaneously added by an expert system which is helpful for managing reservoirs. Using an expert system is recommendable for assessing simultaneous impacts of water quality and quantity on the aquatic habitats.

*Many methods and different types of models have been used in the environmental flow assessment which help engineers to manage different case studies. One method is not useable in all cases due to specific environmental requirements and technical limitations which implies applying different linked method in the environmental management of a diversion dam or reservoir is needed. This thesis covered a wide range of advanced methods of environmental flow optimization which is a significant advantage in practical applications.

* Previous studies developed some frameworks to incorporate climate change impacts with the reservoir operation. However, these were not efficient to integrate all environmental and economic impacts in the operation optimization. This thesis proposed a simulation-optimization which integrates water and energy use with a focus on agriculture because many dams have been constructed to satisfy irrigation demands.

## 10.2 Recommendations

*The proposed methods should be used based on the technical considerations in real life cases. Hence, environmental impacts in each case should be discussed by the regional experts before applying the methods in practice. It is recommendable to highlight regional technical issues in future studies.

*Upstream environmental impacts of reservoirs are not integrated in the simulation-optimization frameworks which means future studies should highlight the upstream environmental impacts as well.

*Impact of climate change is not the same in all cases. Hence, it is recommendable to investigate the global warming impacts on each river basin independently.

*We added economic aspects with a focus on agricultural activities. However, it is needed to add other socio-economic indices to the simulation-optimization approaches. Thus, it is recommendable to add other socio-economic indices as well.

*In some river basins, surface water and ground water may interact affecting water supply. Hence, it is needed to integrate the proposed methods with the groundwater models to cover all aspects of water supply in these basins.

*We compared the proposed ecological methods with the Tennant method for assessing environmental flow. However, it is recommendable to compare the results in future studies with dynamic e-flows such as 10% $Q_{Daily}$

*All used tools in this research work are improvable which means there is ample room for future studies to improve efficiency of the developed frameworks.

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