PUMP SCHEDULING ENERGY OPTIMIZATION MODELS FOR DRINKING WATER DISTRIBUTION SYSTEMS

A Thesis

by

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MASTER OF SCIENCE IN ENERGY

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ABSTRACT

Drinking water distribution systems (DWDS) in the United States utilize approximately 2% of the nation's total energy (DOE, 2021). The 2014 US Department of Energy (DOE)Report states 39.2 billion kWh energy is used in drinking water distribution systems (DWDS) pumping and aeration (DOE, 2014). If optimization techniques were implemented and the energy consumption were to be reduced by 10%, the saving would equate to 3.14 billion kWh annually (Mohsen, 2016). As DWDS continue to face challenges in water scarcity and rising energy cost, DWDS have shown an interest in improvement through the application of modern data science tools. This study performs a proof of concept on a coupled hydraulic and optimization model method to support engineers in optimization analysis. The joined Water Network Tool for Resilience (WNTR) hydraulic model and EPANET supports analyses through minimizing user error, automating manual processes, and increase efficiency. The WNTR hydraulic tool coupled with optimization algorithms provides hydraulic engineers an invaluable tool. The tool allows users unlimited flexibility in the desired algorithm applications and tuning parameters, which allows researchers to effectively quantify results and identify the best algorithmic approach

DEDICATION

I want to thank my husband, George, who always encourages me toward my goals and believes in me. Also, I want to thank my mentors throughout my career that have passed along decades of valuable experience and led with kindness and excellence. Lastly, I want to thank my thesis committee for helping me pursue a thesis topic related to a field I am passionate about and supporting me through my education.

CONTRIBUTORS AND FUNDING SOURCES

Contributors

This work was supervised by a thesis committee consisting of Dr. Pistikopoulos and Dr. Pappa from the Energy Institute at Texas A&M University, Dr. Mohtar from the Department of Biological & Agricultural Engineering and Civil Engineering at Texas A&M University, and Dr. Avraamidou with the Department of Chemical and Biological Engineering the University of Wisconsin Madison.

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NOMENCLATURE

AWWA	American Water Works Association
ANN	Artificial Neural Network
BEP	Best Efficiency Point
DDA	Demand Driven Analysis
DOE	The United States Department of Energy
DP	Dynamic Programming
DWDS	Drink Water Distribution Systems
EA	Evolutionary Algorithm
EPS	Extended Period Simulation
GA	Genetic Algorithm
GHG	Greenhouse Gas
HI	Hydraulic Institute
HW	Hazen-Williams
LP	Linear Programming
MINLP	Mixed Integer Nonlinear Programming
MILP	Mixed Integer linear Programming
NLP	Nonlinear Programming

PDA	Pressure Driven Analysis
PPI	Pump Performance Index
TCEQ	Texas Commission of Environmental Quality
TDH	Total Dynamic Head
WNTR	Water Network Tool of Resilience
WRF	Water Research Foundation
VSD	Variable Speed Drive

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1. INTRODUCTION

This research paper focuses on identifying optimization tools and methods to support DWDS pump schedules optimization to minimize energy consumption. Researchers estimate DWDS pump scheduling energy can be optimized by 10%. DWDS have interest in optimization throughout the system due deteriorating infrastructure, decrease availability in natural resources, and increasing energy rates. First, a literature review summarizes the general concept of hydraulic modeling, optimization components, optimization methods, and an overview of related studies in the last five decades. Studies on DWDS Optimization began in 1970 due to emerging hydraulic modeling software tools and have since increased in complexity and frequency. Second, the pump schedule optimization methodology is presented. The objective function formula for minimizing energy consumption, pump schedule decision variables, and system pressure constraints are introduced. The hydraulic and optimization models are coupled through several software's tools, such as Python, Jupyter Notebook, EPANET, and WNTR. A pseudo code is presented to demonstrate the process logic and flow. Third, the coupled hydraulic and optimization model tool is presented in detail. Last, final concluding remarks on the effort and identified future research are presented.

1.1 Industry Background and Need for Pump Energy Scheduling Optimization

DWDS and wastewater system in the United Stated utilized approximately 2% of the nation's total energy (DOE, 2021). The 2014 US Department of Energy (DOE)Report states 39.2 billion kWh energy is used in DWDS pumping and aeration (DOE, 2014). If optimization techniques were implemented and the energy consumption were to be reduced by 10%, the saving would equate to 3.14 billion kWh annually (Mohsen, 2016). Further, energy savings could be related to equivalent emission rate per kWh generated. The energy saving related to prevent of greenhouse gasses (GHG). This study solely focuses on energy optimization, but the relate GDG prevention is noteworthy.

Furthermore, an ongoing challenge in DWDS is the ability to benchmark performance of a given pump station. A 2019 study managed by the Water Research Foundation (WRF) and advised by the DOE, gathered data from 18 water utilities worldwide to create a standard benchmark method (Smith, 2019). The data included 48 pumps stations and 177 pumps. A pump performance index (PPI) was presented to normalize pump performance. PPI included efficiency limitation, where total dynamic head (TDH) maximum efficiency is reached at 92% and 2.725 kWh/ML/m. Figure 1 shows the performance the real system pump performance. It is clear from the figure efficiencies in pump performance can be improved. Several researchers estimate DWDS optimization techniques could provide at minimum 10% reduction in annual energy costs (Jamieson, Shamir et al. 2007); (Abiodun and Ismail 2013).

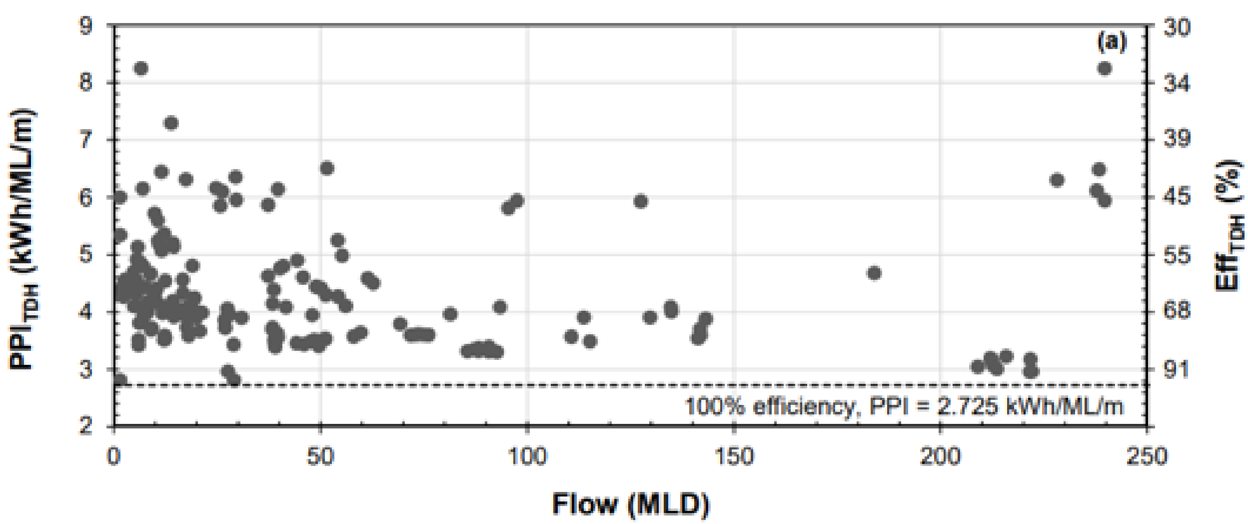


Figure 1.1 PPI Water Utilities (Smith, 2019)

There is a current gap in existing technologies and application in DWDS. A survey found 10% of DWDS metered data is utilized regularly, yet 80% of the water utilities expressed an interest in utilizing data science applications, such as Machine Learning and Optimization Tools, and perform real-time analytics within the next few years (Kadiyala, 2018). The water industry has shown an increased interest in smart technologies, which integrates real-time hydraulic modeling with "big data" management and IoT. Much of the water sector has not implemented "smart" hydraulic modeling technologies, but a few utilities have done so due to the high cost and risk associated with limited water supplies.

2. LITERATURE REVIEW

Several operation optimization methods have been studied for DWDS pump operations since the 1970s, such as linear programming, nonlinear programming, dynamic programming, and meta-heuristic methods. Hydraulic simulation and optimization models coupled could provide engineers valuable information for system operations. The following sections provide a comprehensive literature review on publications related to minimizing energy consumption and related costs through coupled hydraulic and optimization models.

Pump optimization is dependent on proper design and operation. This study focuses on optimal pump operation. Pump design and operation cannot exist independently. A high-level review on best practices for pump design and common mistakes can be referenced Appendix A.

2.1 DWDS Hydraulic Simulation

Hydraulic modeling software performs steady state or extended period calculation analyses, where the before of a pressure node is simulated. The system included a network of pipes, nodes, pump, values, storage tanks, and reservoirs. Hydraulic models are utilized as tools to support DWDS engineers. Two common uses included support for current operations and planning future design. Literature studies on pump schedule operations often utilize the EPANET simulations. EPANET is widely recognized and utilized open-source hydraulic modeling software. The EPANET user interface is shown in Figure 2. Due to computational inefficiencies, hydraulic modeling has also been replaced by artificial neural networks (ANN). Several other methods have been utilized in literature, such as hydraulic equations, GRA-NET based on gradient method, and newton-Raphson. Several studies do not specify the method utilized. Overall, EPANET is most utilized within literature.

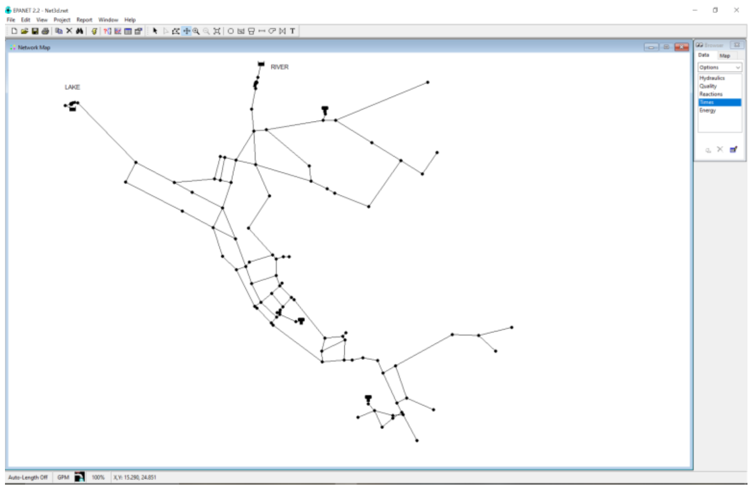


Figure 2.1 EPANET User Interface (EPA)

2.2 DWDS Pump Schedule Optimization

2.2.1 Objective, Decision Variable, & Constraints

A literature review performed by Mala-Jetmarova (2018) evaluated 128 papers on DWDS different optimization objectives from 1977 through 2017. The study identifies DWDS common design problems, the general classifications throughout optimization publications, and future research studies. DWDS fall within two categories; new or existing systems, where system optimization related to strengthening, expansion, and rehabilitation may be beneficial. DWDS optimization relates to either system design or operations. The subcomponents to DWDS include pipe, valves, tank, and pumps.

Figure 3 shows the breakdown of publications focused on design or operation optimization models. The categories include Design at 41%, Strengthening at 25%, Operation at 16%, Expansion at 9%, and Rehabilitation at 9% of total publications reviewed. The limited studies on rehabilitation and expansion may be attributed to strict design constraints often associated with a heavily developed and highly populated areas. Optimization models related to operations have historically been limited to due to computational power and existing algorithms. A DWDS hydraulic operations are non-linear in nature. Nonlinear programming (NLP) methods were rarely utilized by water utilities through the 1970s and 1980s due to challenges with computational power, but utilization have increased in popularity since the 1990s due technological advancements in hardware processing and improved algorithms.

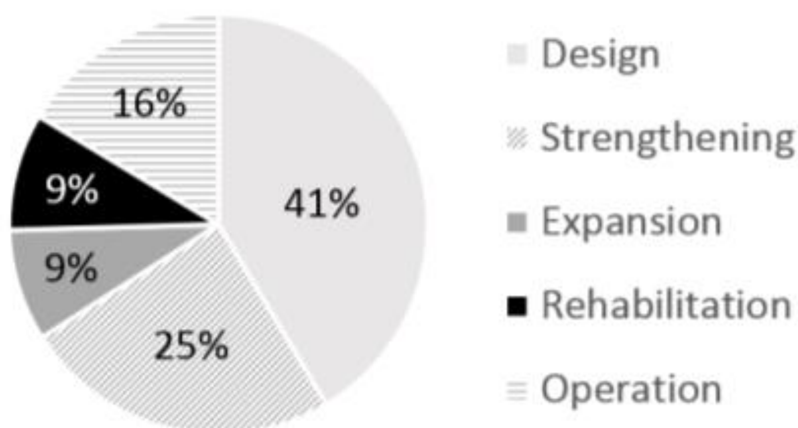


Figure 2.2 DWDS Optimization Application Areas (Mala-Jetmarova, 2018)

An optimization model is comprised of 1) objective functions, 2) decision variables, and 3) constraints. Figure 4 shows the breakdown of objectives, constraints, and decision variables per the 12 publications reviewed by Mala-Jetmarova (2018). The single objective approach returns one optima solution, which provides simplicity to the decision-making process. The multi objective approach returns a set of trade off, or Pareto, solutions, which increase complexity and requires post processing.

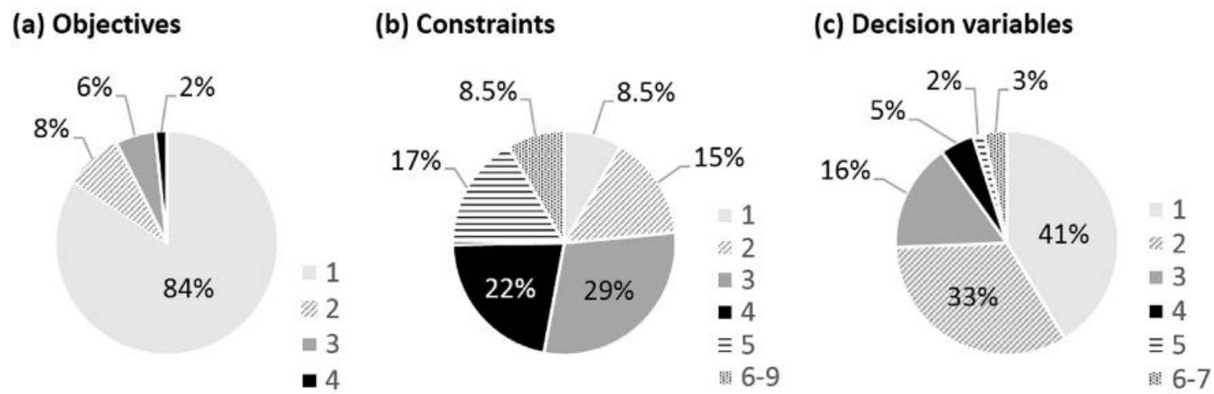


Figure 2.3 Optimization Model Formulation by: (a) Number of objectives, (b) number of constraints, (c)number of types of decision variables, in an optimization model. (Mala-Jetmarova, 2018)

2.2.2 DWDS Optimization Methods

The majority of DWDS optimization studies have focused on stochastics methods, such as heuristic and metaheuristic approaches. A popular type of stochastic approach is the Darwin based genetic algorithm. Deterministic methods have been historically utilized less in DWDS application but have increased in the recent years due to improvement in computation power. Deterministic methods include mixed integer linear programming (MILP) and nonlinear programming (MINLP). Figure 5 shows the breakdown on optimization model categories used in literature related DWDS.

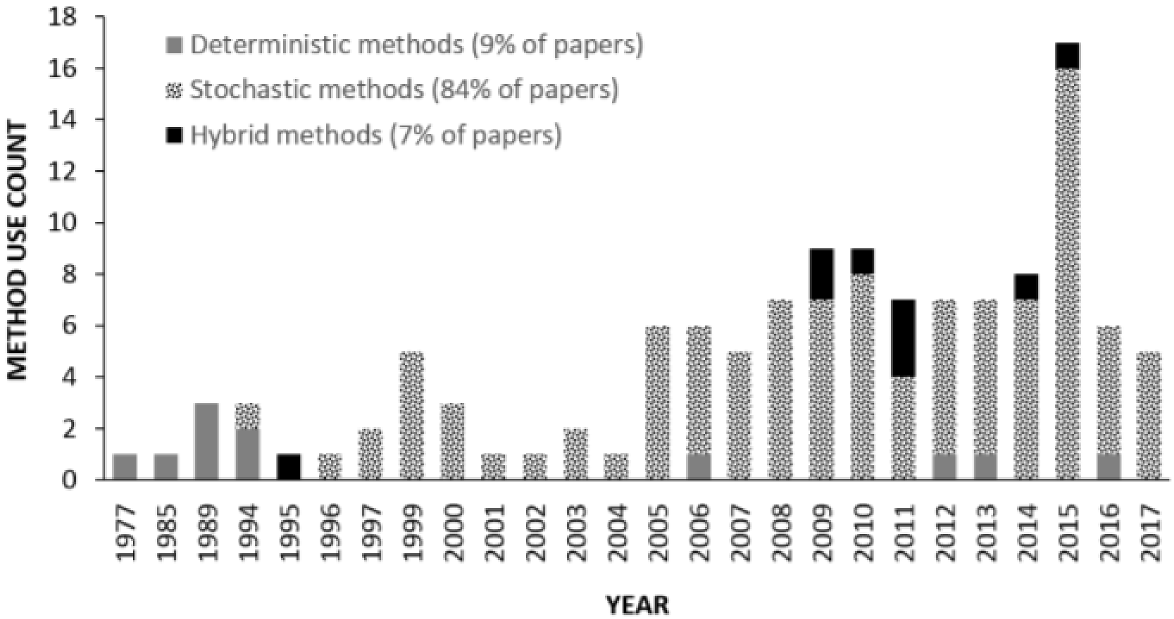


Figure 2.4 Optimization Methods by Year (Mala-Jetmarova, 2018)

Linear programming (LP) has recently increased in popularity for optimizing DWDS pump operations. MIP is often utilized to determine optimal schedule and the method has been applied for optimal pump operations throughout literature. Throughout literature on DWDS pump operational optimization the computation struggles related to MINLP are addressed through an approximate MILP solution, where the non-convex constrains, such as pressures throughout a system, are approximated through a piecewise linear function. A large potential risk with LP is the loss of data through the over simplified linearization of nonlinear hydraulic parameters.

Nonlinear programming (NLP) methods were rarely utilized by water utilities through the 1970s and 1980s due to challenges with computational power, but utilization has increased in popularity since the 1990s due technological advancements in hardware processing and improved algorithms. The method incorporates the realistic characteristic of the variables and promotes greater accuracy in results. A few potential drawbacks associated with NLP include computational difficulties associated to the non-convex pressure dataset and discrete pump operation decision, where a solution may not be obtained as a system increases in complexity and size. The application of MINLP for pump scheduling does not properly scale with increased timesteps and reaches the sizes comparable to real world DWDS (Menke, 2016). A few popular NLP methods are the steepest-ascent or reduced gradient method, Newton-Raphson method, and Levenberg Marquardt method. Additional techniques, such as relaxations and substitutions, may increase computational efficiency.

Dynamic Programming (DP) is a popular optimization method for water utilities. The approach with DP divides the problem into stages with a decision at each stage. The “shortest path” optimization problem follows DP logic. Issues with DP are related the large number of calculations and limitations on the size of the system. Notable studies on pump station operation optimization with DP have been performed by Lansey et. al (1994), Bene et. al (2013), and Kim et al (2015). Recent studies have continued to struggle with the inherent limitation DP places on the allowable system size. Bene et al. (2013) applied a modified approach to DP where model is split into small pieces and the search space is reduced to increase computational efficiency. Kim et al (2015) applied DP and effectively supported a DWDS with 6.3% cost saving to pump operations or a 19.2% cost saving using standby pumps.

Heuristic or Meta-Heuristic methods have historically been popular methods for DWDS analyses. A heuristic method is an applied problem-solving approach that identifies an approximate solution adequate for the required purpose. A heuristic approach is burdened by a large and complex system. Meta-Heuristic genetic algorithms, a subset of Darwinian evolutionary programs, have been used for series of pump on/off decisions to minimize cost. Genetic algorithms operators include crossovers and mutations. A generic algorithm utilizes a combination of possible solutions, where each the solution is comprised of binary or continuous values. Figure 6 illustrated the components of a genetic algorithm.

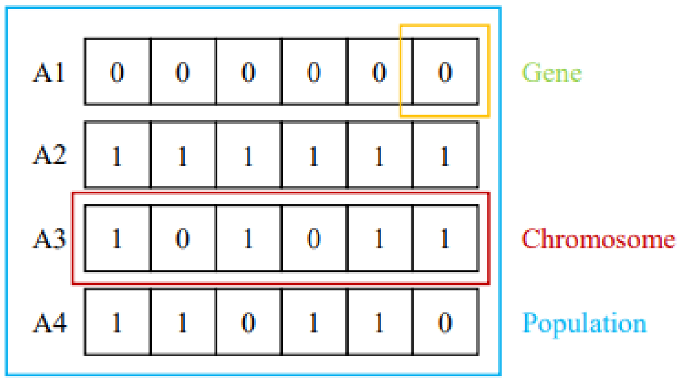


Figure 2.5 Population, gene, and chromosome (Chuang et al., 2015)

The set of all given possible solutions is called the generation. The first-generation set is comprised of random values. The process of natural selection is applied to arrive to the next generation sets. The fitness function and constraints are utilized to determine whether the performance of a given combination. Figure 7 illustrates the logic and progression of a genetic algorithm.

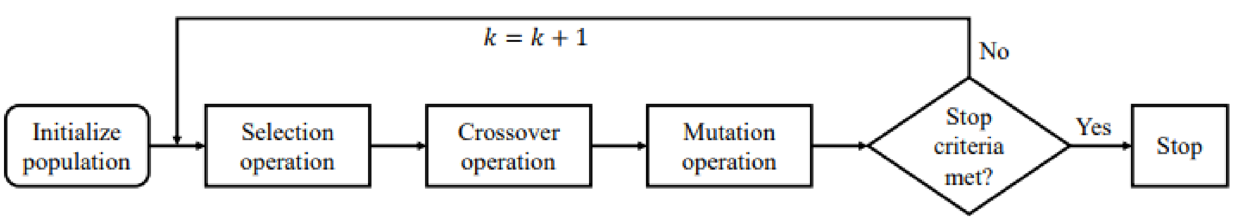


Figure 2.6 Genetic Algorithm Flowchart Scheme (Chuang et al., 2015)

The primary operators in genetic algorithms are crossover or mutation methods. A crossover may incorporate a single point, two-point and k-point, uniform, and ordered method. A mutation may incorporate a flip bit, swap, inversion, and scramble method.

Kelner and Leonard (2003) utilized a genetic algorithm to determine optimal pump operations for fixed and variable speed pumps. Oden et al. (2015) utilized a multialgorithm genetically adaptive method to minimize search space and concluded the method was suitable for real-time controls. In the United Kingdom, a WDS utilized genetic algorithms to support real-time operation logic control. Meta-Heuristics struggle with computation efficiency in large water distribution (Mala-Jetmarova, 2015).

3. METHODOLOGY

The application of hydraulic simulation models for the pump scheduling optimization evaluates the current hydraulic condition of a water utility system and the hydraulic constraints to meet the required consumer diurnal demands.

First, the hydraulic simulation model converges on flow and pressure results and energy is calculated. Second, the optimization model determines a pump schedule combination, and the results are uploaded to the hydraulic model (Ormsbee, 2009). The approach develops a loop between a DWDS hydraulic simulation model and an optimization model. The network simulator solves for the hydraulic constraints and the optimization. The process is illustrated in the Figure 8 below. The optimization model solves for the optimal solution given the hydraulic and operational conditions.

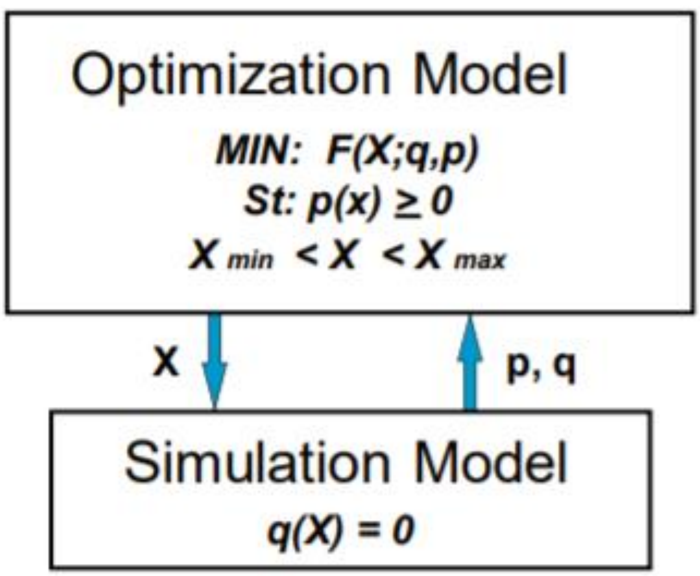
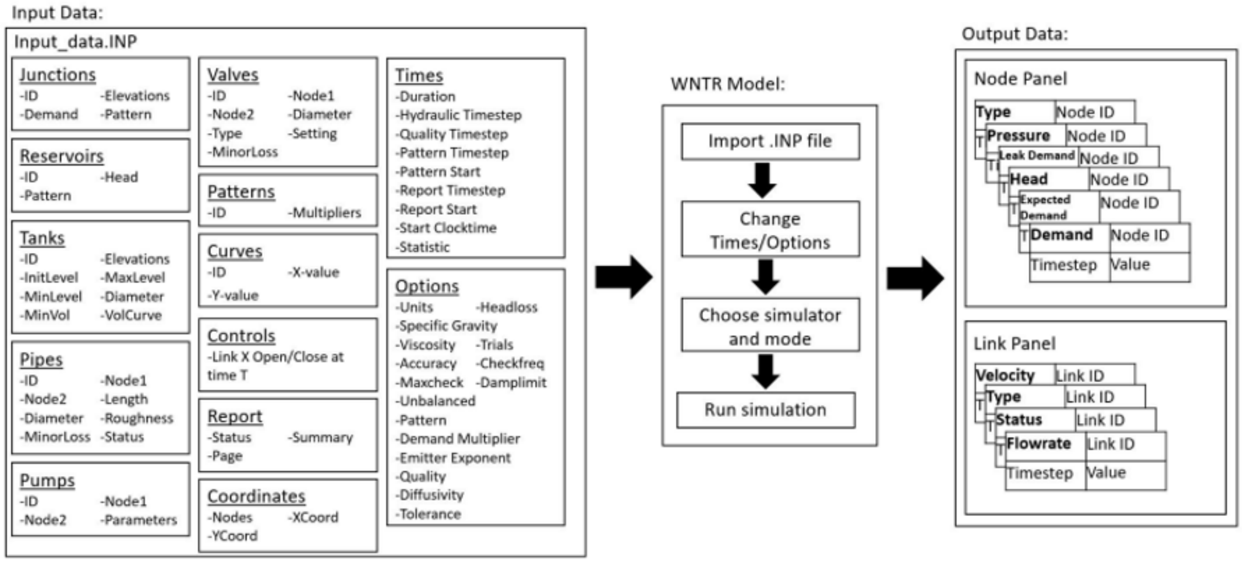


Figure 3.1 Optimization & Hydraulic Model Loop (Walksi, 2003)

The study incorporates various tools to perform the simulation and optimization loop analysis. The tools include Python, Jupyter Notebook, EPANET, and WNTR. The python module “Platypus” was selected over existing python libraries “PyGMO”, “Inspyred”, and ”SciPy” due to the multi objective capabilities. The study focuses on a single objective, but “platypus” gives the option to further extend the analysis. A brief summary on EPANET and WNTR are provided below.

EPANET is a public domain hydraulic simulation software developed by the United States Environmental Protection Agency (EPA). The application is intended to support DWDS. “Today, engineers and consultants use EPANET to design and size new water infrastructure, retrofit existing aging infrastructure, optimize operations of tanks and pumps, reduce energy usage, investigate water quality problems, and prepare for emergencies” (EPA, 2021). The study utilized EPANET Example 3 available on GitHub online, which has been extensively utilized through literature.

The Water Network Tool for Resilience (WNTR) is an open-source python package for hydraulic simulation first released in 2016 by the EPA and the Department of Energy’s Sandia National Laboratory. The python package allows for seamless transfer of EPANET input file data to Python. The process is illustrated below in Figure 9, where EPANET input data file is uploaded, and the hydraulic simulation computed within Python. WNTR is compatible with EPANET 2.2, and Python 3.8. Common python tools can be utilized with WNTR, such as Pandas, NumPy, SciPy, and Matplotlib. WNTR may be downloaded through GitHub online.



WNTR imports input data in a standard, EPANET format that includes supply, demand, and network attributes for the WDN. WNTR executes a time-step simulation and produces two output files containing information about the behavior in the nodes and links of the network.

Figure 3.2 WNTR Framework (Bunn, 2018)

3.1 DWDS Hydraulic Simulation

The study utilized EPANET Example 3 available on GitHub online, which has been extensively utilized through literature. Figure 10 shows a schematic of the system. EPANET Example 3 included 92 junctions, 2 reservoirs, 3 tanks, 116 pipes, 2 pumps, and 0 valves. Hazen-Williams (HW) headloss formula was utilized. The analyses were a 24-hour extended period simulation (EPS) with a 1-hour timestep.

Figure 3.3 EPANET Example 3 Schematic (EPA)

Furthermore, WNTR converts all units to International System (SI). The proper unit for all data is provided below:

- Length = m
- Diameter = m
- Water pressure = m (this assumes a fluid density of 1000 kg/m3)
- Elevation = m
- Mass = kg
- Time = s
- Concentration = kg/m3
- Demand = m3/s
- Velocity = m/s
- Acceleration = g (1 g = 9.81 m/s2)
- Energy = J
- Power = W
- Mass injection = kg/s
- Volume = m3

3.2 DWDS Pump Schedule Optimization

3.2.1 Objective, Decision Variable, & Constraints

Equation 1 express the objective function to minimize energy in relation to pump schedules. expresses energy consumption in kWh and accounts for time duration. Pump energy usage directly relates to flow, head, and time duration. Pump energy usage inversely relates to the efficiencies.

$$\min f(x) = E_{Total}(x) \qquad \text{(Eq. 1)}$$

Equation 2 expresses energy consumption in kWh and accounts for time duration. Pump energy usage directly relates to flow, head, and time duration. Pump energy usage inversely relates to the efficiencies. "The energy use is specific to each operating point of the pump; therefore, to determine the total energy use of the pump in a give period, the energy uses that occur at each operating point within the period should be summed "(Smith, 2019) as shown in the following equation.

$$E_{Total} = \sum_{i=1}^{N} \left(\frac{Q*H}{\eta_p*\eta_m*\eta_D}\right) * t_i \qquad \text{(Eq. 2)}$$

Where,
Q = flow,
H = head,
η_p *= pump efficiency %,*
η_m *= motor efficiency %,*
η_D *= drive efficiency %, and*
t = simulation time duration.

Furthermore, the total combined efficiencies may be expressed as the water-to-wire efficiency shown in Equation 3 below.

$$\eta_{ww} = \eta_p * \eta_m * \eta_D \quad \text{(Eq. 3)}$$

The wire-to-water efficiencies are assumed to follow average values shown in Table 1 (Smith, 2019). EPANET WNTR user manual recommends the water to wire efficiency of 0.75. This study utilized the lower value between the two sources at 0.67 for the water-to-water efficiency value.

Table 3.1 Conceptual Calculation of the Efficiencies (Smith, 2019)

Efficiency	Low	Medium	High
Pump Efficiency	65	75	85
Motor Efficiency	95	95	95
Pump & Motor	62	67	81

The decision variable relates to the pump status (on/off) and combination. The schedule vector is passed into the simulation model, the simulation runs, and the pressure results are passed the optimization model. The model has 1 hour time steps and total duration of 24 hour or 1 day. The pump schedule combination considered the possible binary on/off status of each pump. Pumps with variable speed drives (VSD) were not considered in this study. Figure 11 provides an example of the pump scheduling vector.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Pump 1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	0	0	0	1	1	0	0	0	0
Pump 2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1

Figure 3.4 Pump Schedule Combinations (Chuang et al., 2015)

The hydraulic simulation model represents a digital copy of the water distribution system field condition, which incorporate most hydraulic constraints:

- Pipe: Diameter, Length, Roughness Coefficient (Hazen-Williams)
- Nodes: Elevations
- Valves: Type, Size, CV Flow Curve
- Appurtenances (i.e., Valves, Fittings): Friction Losses
- Source Flow/ Reservoirs
- Time Varying Base Demands
- Base Demand and Daily Usage Pattern (Diurnal Patterns): Wholesale, commercial, industrial, irrigation, residential
- Storage Tanks: Volume Size, Dimensions
- Pumps: Capacity, Flow and Efficiency Curves
- Pressure Planes/ Hydraulic Zones

Furthermore, EPANET allows for demand driven (DDA) and pressure driven analyses (PDA). The default setting for the program is DDA, where the demands must be delivered regardless of pressure conditions. The DDA hydraulic simulations setting was utilized for the study. In order to match real conditions, DDA meets the used defined demand conditions and acceptable pressures within the system must be maintained. The Texas Commission of Environmental Quality (TCEQ) minimum pressure requirements for DWDS is 35 psig per the

Title 30 Texas Administration Code (30 TAC) Section 290.444. This study followed the TCEQ requirement and incorporated the constraint where pressures must be equal to or greater than 35 psig and the system demands are met.

3.2.2 Genetic Algorithm Application

Python libraries were installed through “pip” tool for python. The decision variable for the problem is the pump status on/off throughout a 24-hr time horizon, which is represented by binary integer values of 1 or 0. This is known as the chromosome representation. The chromosomal representations are mapped to the solution through a fitness function. The constraint of a problem can be classified as hard and soft constraints.

4. ANALYSES & RESULTS

4.1 Simulation & Optimization Model, Proof of Concept

The following section outlines the pseudo code for the developed tool to support pump scheduling optimization. Appendix B present the python code providing a proof concept. There is limited amount of literature on the novel EPANET-WNTR and GA approach. It is recommended extend study to contain additional decision variables and be applied to larger systems.

A pseudo code outlining the required intermediate set was developed to support building the final python script for models. The pseudo code is provided below.

a. Hydraulic Model Function

   Note: The key objective is to obtain energy consumption.

   - Obtain Flowrate
   - Obtain Head
   - Calculate Energy

b. New Pattern Function

   Note: The Key Objective is to pass the new pump schedule to hydraulic model

   - Upload hydraulic file
   - Modify pump schedule
   - Simulate hydraulics (Utilize function above to compute energy)
   - Identify the minimum pressures in system

c. Execute Genetic Algorithm

- Provide data on hydraulic file
- Identify pump, pump pattern id, and critical nodes
- Genetic Algorithm will pass new pump schedules
- Energy is calculated through steps a and b

The final python script product developed is provided in Appendix B.

4.2 DWDS Pump Optimization Future Research

The complexity of DWDS cannot be overstated. The use of data science tools, such as simulation models, optimization models, machine learning, and artificial intelligence can support DWSW implement sustainable design and operations through the system. Figure 12 shows a study identified the following categories for DWDS optimization improvement. Identified categories include model inputs, algorithm and solution methodology, search space and computation efficiency, and solution post processing.

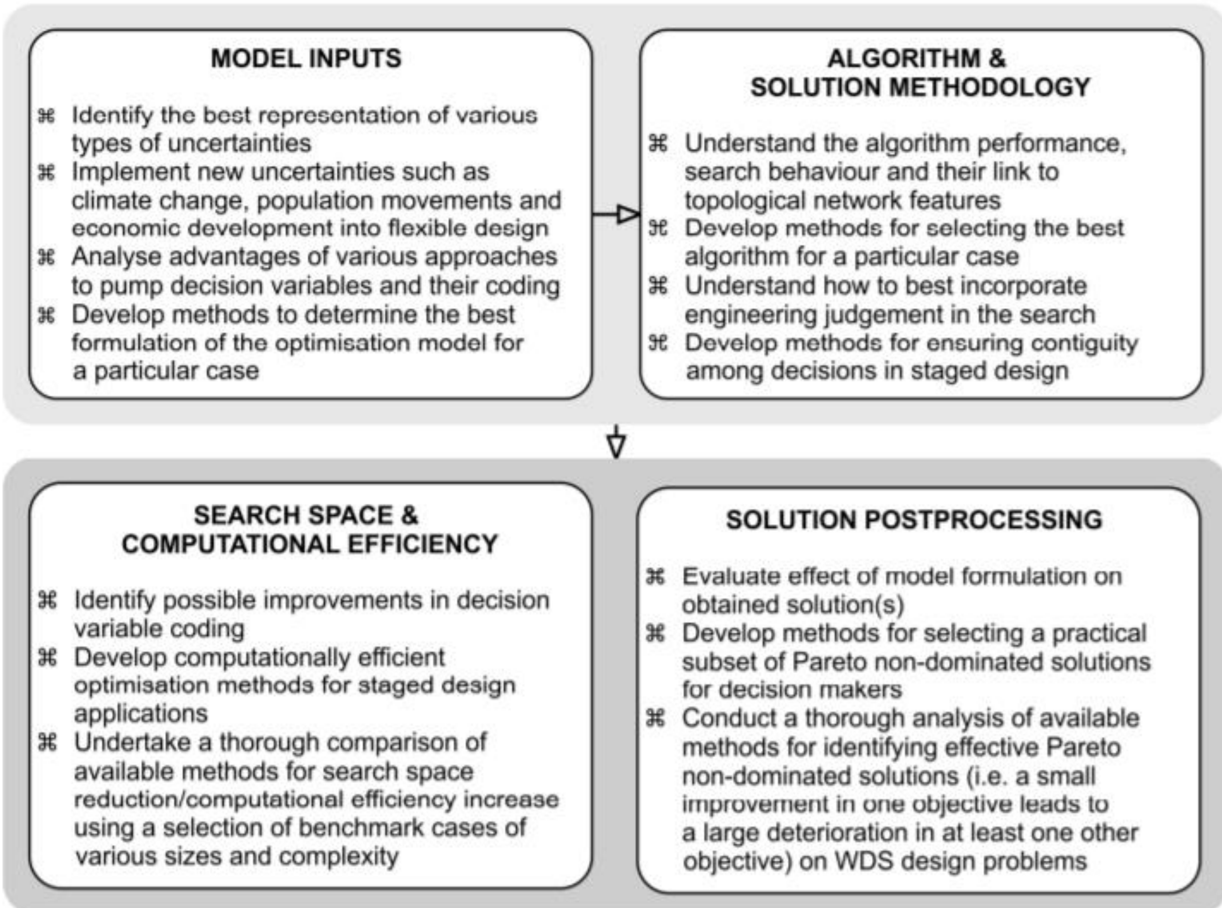


Figure 4.1 Future Research Challenges (Mala-Jetmarova, 2018)

For example, the majority of literation operation optimization is limited in the number of objective function and decision variables. Furthermore, the majority of study model small in comparison to real world models. Additionally, studies fail to within the industry. And they fail to incorporate Figure 13 shows the breakdown of test DEDW Network Size. The networks studied are small in comparison to real cities. The commercial software Bentley Water GEMS estimates 1000 pipes are required for every 10,000 population.

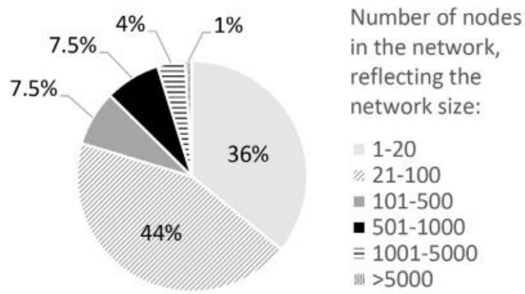


Figure 4.2 Test DWDS Network Size (Mala-Jetmarova, 2018)

Literature has a limited number of studied on pump scheduling optimization DWDS. Few studies have reviewed the performance of pump control, whether on/off or VSD. Additionally, studies on pumps with throttle control vales or bypass control. Throttle control vales can be values asset support pumps to operate closed to the design BEP in the case the pump was originally over design and sized too large. Figure 14 shows scenarios to consider in pump schedule optimization. Pump schedules and throttled valves percent opening may be both considered for energy optimization.

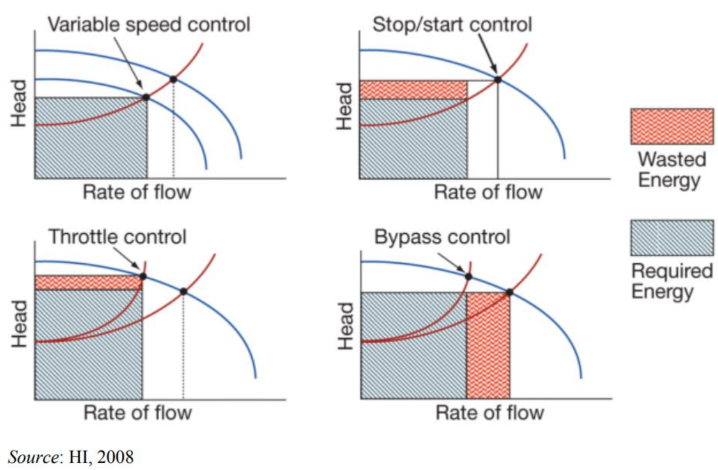


Figure 4.3 DWDS Pump Considerations for Optimization (Smith, 2019)

Machine learning methods, such as, Artifical Nueral Networks(ANN) have been eveloepd to reperesent the hydraulic surrogate model. ANN have the ability to accurtately reprenstne complex and non-linear systems. The reason to use ANN's is the computation time is significationly faster than a hydraulic simualtion. These metamodels do not perform energy or mass balance computations, but trained to handle DWDS inputs and genreate outputs as shown in Figure 15.

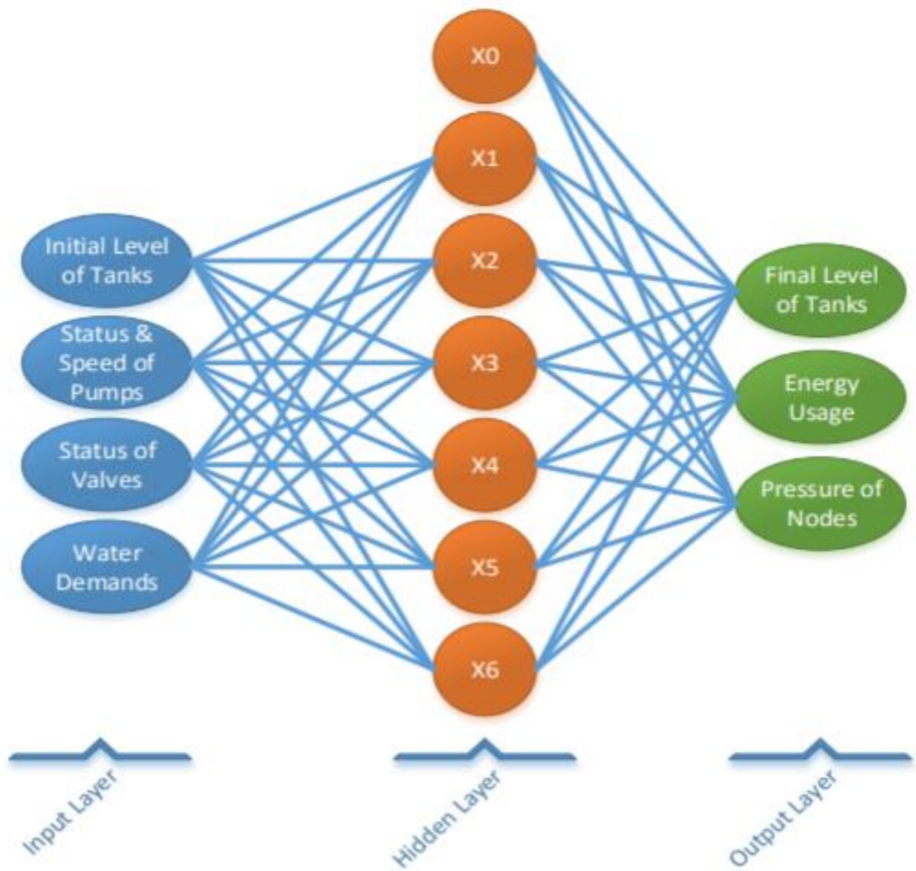


Figure 4.4 Schematic of ANN for DWDS (Abkenar, 2016)

5. CONCLUSION

The application of optimization model for DWDS for pump scheduling has been explored for decades, but methods continue to face various challenges in feasible solutions for large complex systems. The 2016 release of WNTR allowed hydraulic engineers to perform analyses in conjunction with Python and Python processing tool. The joined WNTR hydraulic model and EPANET supports analyses through minimizing user error, automating manual processes, and increase efficiency. The WNTR hydraulic tool coupled with optimization algorithms provides hydraulic engineers an invaluable tool. The tool allows users unlimited flexibility in the desired algorithm applications and tuning parameters, which allows researchers to effectively quantify results and identify the best algorithmic approaches.

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APPENDIX A

Pump sizing and scheduling play a large role in the energy optimization of water utilities. Historically, the key objective in pump selection was to meet consumer demands and limited to readily available, “on the shelf”, pre-manufactured equipment with low “front-end” cost (Karassik, 2008). The information age has promoted greater communication between the engineer and manufacturer and improved the pump selection process, yet aged infrastructure remains in the field.

A hydraulic model with seasonal demand scenarios can be utilized to determine if the pumps are designed properly and the system can obtain higher levels of efficiency. Pumps incorrectly sized in the design process have little margin for increased optimization. Oversizing pumps is a common error in the pump selection process. The projected future maximum consumer demands are overestimated, and the minimum consumer demands are often overlooked. It is critical to incorporate the minimum consumer demands. Projected consumer demand is often based on census data and population studies. The pump’s operational flexibility must be considered, where pump performance is evaluated at the projected maximum and minimum consumer demands through the estimated pump life expectancy.

In addition to optimal efficiency, a pump sized incorrectly will encounter mechanical problems. Common consequences are pump cavitation, internal recirculation, poor flow control, excessive maintenance, and frequent bearing replacement. In situations where the pump has been sized inaccurately, a life cycle cost (LCC) assessment must be conducted to evaluate if replacement or rehabilitation make economic sense. The water industry has access to extensive support tools for pump selection and LCC, which include resources developed for municipalities. The United States Department of Energy (DOE) and the Hydraulic Institute (HI) partnership offer free resources and tools online, such as the HI “Pump Unit Energy Saving Measures” spreadsheet.

APPENDIX B

IMPORT LIBRARY

In [1]:

```
#IMPORT LIBRARY
import time
import sys
import wntr
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from wntr.network import Tank, Pipe, Pump, Valve
import logging
import scipy
from platypus import NSGAII, Problem, Binary, nondominated
import geneticalgorithm as ga
```

SUPPORT FUNCTIONS

In [2]:

```
# UPLOAD INP FILE TO WNTR SIMULATION (FOR OBJ FUNC)
def open_file (inp_file:str):
    wn = wntr.network.WaterNetworkModel(inp_file)
    return wn

# SIMULATE HYDRAULICS (FOR OBJ FUNC)
def run_epanet_simulation(wn):
    sim = wntr.sim.EpanetSimulator(wn)
    results = sim.run_sim()
```

In [3]:

```
# EXTRACT PRESSURE TIME SERIES (FOR OBJ FUNC)
def pressure_series(results, node_id:str):
    pressure_seri = results.node['pressure'].loc[:,node_id]
    return pressure_seri
```

In [4]:

```
# RETURNS EXISTING PATTERN VALUES (FOR OBJ FUNC)
def pattern_values_list(wn, pump_pat_id:str):
    pat = wn.get_pattern('pump_pat_id')
    return pat.multipliers

#REPLACE PATTERN VALUES WITH A NEW PATTERN (FOR OBJ FUNC)
def modify_pattern(wn, pump_pat_id:str, new_pattern:str):
    pat.multipliers = new_pattern
    return
```

In [5]:

```
# CALCULATE ENERGY CONSUMED BY PUMP (KWH) (FOR OBJ FUNV)
def energy_consumption(wn,results,pump_id:str, t_step = 3600):
    #HEAD & FLOW
    pump_flowrate = results.link['flowrate'].loc[:,wn.pump_name_list]
    head = results.node['head']

    #POWER TIME SERIES (KW)
    pump_energy_series = []
```

```
    for i in range(0,t_step*24,t_step):
        energy = wntr.metrics.pump_energy(pump_flowrate, head, wn).loc[i,pump_id]/1000
        pump_energy_series.append(energy)

    #ENERGY (KWH)
    pump_energy = sum(pump_energy_series)

    #POWER TIME SERIES (KW) & ENERGY (KWH)
    return pump_energy, pump_energy_series
```

OBJ FUNC + CONSTRAINTS

In [6]:

```
# CALCULATE ENERGY CONSUMPTION FOR INPUT OF NEW PUMP PATTERNS LIST

def objective_func(file,new_pattern:str,pump_pat_id:str, pump_id:str, critical_nodes:st

    # UPLOAD INP FILE TO WNTR SIMULATION (FOR OBJ FUNC)
    wn = open_file(inp_file)

    #REPLACE PUMP PATTERNS
    modify_pattern(wn,pump_pat_id,new_pattern)


    #SIMULATE HYDRAULICS (FOR OBJ FUNC)
    results = run_epanet_simulation(wn)

    #CALCULATE ENERGY
    for pump in pump_id:
        energy = energy_consumption(wn,results,pump)
        total_energy += energy
    return total_energy

    #EXTRACT MIN TIME SERIES PRESSURE
    P_at_cr_nodes = []
    for critical_node in critical_nodes:
        pr = min(pressure_series(results, critical_node))
        P_at_cr_nodes.append(pr)
```

OPTIMIZAITON MODEL

In [7]:

```
start_time = time.time()

def Optimize_Pump_Schedule(x):

    #DATA
    inp_file = r'C://Users//Paola Holleway//Desktop//Untitled Folder//Net3e.inp'
    pump_id = ('10')
    pump_pat_id = (['6'])
    new_pattern = [element for element in x]
    critical_nodes = ('123','15','35','203') # Those nodes expected with large drop in 


    #PRESSURE REQS
```

```
min_P_req_at_cr_nodes = [1.5 for j in range(len(critical_nodes))]


#ENERGY
Energy = np.round(objective_func(inp_file, pump_pat_id, new_pattern,  pump_id, crit
return [Energy]
```