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Original article

OPTIMIZATION OF WATER DISTRIBUTION SYSTEM USING SIMPLEX ALGORITHM ON MICROSOFT EXCEL

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ABSTRACT

This study applies the Simplex linear programming (LP) algorithm—implemented using Microsoft Excel Solver—to optimize a simulated water distribution system (WDS) through an accessible and fully reproducible spreadsheet workflow. The model represents a hypothetical urban network of 3,650 buildings arranged in a 10 × 10 grid (100 junctions, 180 pipes), and seeks to minimize installation and operational costs while satisfying hydraulic and design constraints. Hydraulic behavior was computed using the Hazen–Williams equation (C = 150), with optimization performed in Excel Solver's Simplex LP engine and independently cross-validated using the HiGHS optimizer in Python. The optimized configuration, consisting of a 15 m reservoir elevation and 150 mm pipe diameter, reduced the total system cost from USD 375,000 in the baseline design to USD 195,000, achieving a 48% improvement while maintaining acceptable head-loss (5.59 m ≤ 20 m) and velocity (0.85 m/s within the 0.3–2.5 m/s recommended range). Although the model is limited to steady-state hydraulics, uniform pipe diameters, and simplified friction assumptions, its transparency, low computational requirements, and ease of implementation make it well suited for academic instruction, rapid preliminary design, and resource-constrained municipal environments. Sensitivity analysis (±10–15% demand; ±10% Hazen–Williams roughness coefficient C) indicates that the optimal design is robust under moderate parameter uncertainty. Future research will integrate EPANET for nonlinear hydraulic verification and extend the approach to larger networks and multi-objective optimization.

KEYWORDS: Simplex Algorithm; Microsoft Excel Solver; Linear Programming in Hydraulic Modeling; Water Distribution System; Cost Optimization.

1. INTRODUCTION

Water distribution systems (WDSs) are critical infrastructure for urban environments, ensuring the reliable delivery of potable water to residential, commercial, and public facilities. Designing such systems requires balancing hydraulic performance, construction costs, energy requirements, and regulatory constraints. Traditional optimization of WDS layout and sizing typically relies on specialized hydraulic software or advanced nonlinear and metaheuristic algorithms, which may be inaccessible in many academic institutions, small municipalities, and resource-constrained engineering settings. Consequently, there is a growing need for practical, transparent, and widely available optimization tools that can support teaching, preliminary design, and decision-making in such contexts.

Linear programming (LP) provides a mathematically rigorous and computationally efficient framework for minimizing costs subject to engineering constraints. The Simplex method remains one of the most widely used LP approaches, and its implementation in Microsoft Excel Solver enables engineers, practitioners, and students to formulate and solve optimization problems using software they are already familiar with. Despite its simplicity, Excel Solver has been successfully applied in numerous engineering domains, including structural design, resource allocation, environmental modeling, and hydraulic analysis. However, its potential in water distribution system optimization remains underexplored in the literature, especially in terms of reproducible workflows and spreadsheet-based hydraulic modeling.

This study presents a fully transparent Excel-based approach for optimizing a simulated urban WDS using the Simplex LP algorithm. A hypothetical grid network of 3,650 buildings (100 junctions, 180 pipes) is modeled to minimize total installation and operational costs subject to hydraulic and design requirements. The hydraulic model is based on the Hazen–Williams equation, and the optimization results are validated

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using Python's HiGHS LP solver to ensure accuracy and reproducibility. The study further evaluates the robustness of the optimized design through parameter sensitivity tests and discusses the suitability of Excel Solver for educational and resource-limited engineering applications. By combining accessibility, methodological clarity, and cross-platform validation, this work demonstrates that even complex engineering optimization tasks can be performed using widely available tools.

2. LITERATURE REVIEW

Hydraulic Modeling and LP Tractability: Water distribution systems (WDS) deliver potable water through networks of pipes, pumps, valves, reservoirs, and tanks. Contemporary modeling frequently adopts steady-state approximations where head losses are represented by empirical relations. The Hazen–Williams equation (Hazen & Williams, 1902) remains a foundational model for steady-state WDS analysis and operational formulations, widely adopted in modern studies, with equality constraints linking inlet–outlet junction heads to friction losses (AWWA, 2017; Shafaei, 2024). Recent work by Gu and Sioshansi (2025) presents an operational modeling framework for the water–distribution and electricity systems nexus, co-locating and coordinating operational decisions across both infrastructures. "Co-locating" involves placing water and electricity infrastructure elements (e.g., pumping stations, storage facilities) in proximity to leverage shared resources and reduce operational costs; and "coordinating" involves synchronizing the operational decisions of both systems (e.g., scheduling water pumping during off-peak electricity hours) to improve efficiency and reliability. This integration improves efficiency by aligning pumping schedules with off-peak electricity tariffs and optimizing spatial placement of facilities, while employing linearized hydraulic models to retain computational tractability. They discuss the computational challenges—particularly the non-linear and non-convex characteristics of WDS—and propose linearization and convexification strategies to make real-time operational coordination tractable. This reinforces the viability of linear formulations like the Simplex algorithm in WDS optimization under broader nexus-focused operational contexts.

Newer studies also revisit the Hazen–Williams coefficient calibration, showing that mis-specification can bias friction head loss by double-digit percentages, underscoring the need for careful parameter choice in any optimization that relies on the Hazen–Williams equation (Shafaei, 2024).

Optimization Paradigms in WDS: Optimization in WDS spans a spectrum from linear programming (LP) and mixed-integer linear programming (MILP) to nonlinear programming (NLP), metaheuristics, and Bayesian/learning-based methods. On the linear side, a 2023 framework, MILPNet, demonstrates that many WDS design and operation problems can be cast as MILP with adjustable structure to accommodate diverse constraints (e.g., capacities, component selection, scheduling), preserving computational tractability and convexity in solution space (Thomas & Sela, 2024).

For operations, recent contributions address pump scheduling and pressure management, balancing energy efficiency and water quality under complex constraints—often formulated as nonlinear or mixed-integer problems—while still revealing linearizable substructures, such as piecewise-linear representations of energy tariffs (Janus *et al*., 2024; Shao *et al*., 2024).

Studies of pressure-reducing valves (PRVs) refine constraint modeling to capture realistic valve behavior, enhancing solution fidelity even when integrated into broader optimization models (Dai, 2024; Dini *et al*., 2022).

Beyond deterministic LP/MILP, Bayesian optimization has been explored for booster disinfection scheduling, offering a data-efficient solution strategy through surrogate modeling that reduces reliance on extensive water quality simulations (Moeini *et al*., 2023).

Metaheuristic methods such as genetic algorithms (GA), particle swarm optimization (PSO), and hybrid approaches remain prevalent for tasks like leakage reduction, network rehabilitation, and multi-objective design, with recent reviews summarizing advances and persisting challenges (Jenks *et al*., 2023).

Reliability and Computational Frontiers: A 2023 bibliometric and scoping review highlights exponential growth in water distribution system (WDS) reliability research, mapping influential resilience strategies, failure modeling techniques, and integration with design optimization (Al-Najjar *et al*., 2023). Concurrently, cutting-edge computational directions such as *GPU-accelerated steady-state estimation and integrated performance–quality optimization* are being explored to speed up hydraulic simulations and enhance solution accuracy—despite the predominantly nonlinear nature of these approaches, they provide context for how linear models are used or approximated in broader system workflows (Luan *et al*., 2023). These developments underscore the importance of transparent formulations; when applicable, linear programming (LP) and mixed-integer linear programming (MILP) remain attractive for their interpretability and computational tractability.

Excel Solver in Engineering Optimization: Although specialized solvers such as Gurobi and CPLEX dominate research practice, *Microsoft Excel Solver* remains widely accessible for linear programming (LP) and integer LP pedagogy as well as small- to medium-scale engineering problems. Microsoft's official documentation confirms that Solver supports LP via the *Simplex Linear Programming* algorithm and can handle a range of constraints and decision variables typical of classical linear programming tasks (Microsoft, 2024). In education and research contexts, several studies demonstrate the continued relevance of spreadsheet-based optimization tools for hands-on LP instruction and applied problem-solving; for example, Excel Solver has been used extensively in teaching LP and transportation problems (Ezeokwelume, 2016; Chandrakantha, 2011). Furthermore, open-access demonstrations published between 2021 and 2024 showcase LP problems solved with Excel's Solver in applied settings, reinforcing its relevance for demonstrative and replicable optimization projects.

Positioning Note: While many Excel-Solver engineering case studies (e.g., distillation sequences, heat-exchanger networks) predate 2020, the 2020–2024 literature continues to endorse Excel as a viable platform for teaching and illustrating Simplex LP—an approach that aligns directly with the pedagogical aim of this study. Unlike CPLEX, MILPNet, which requires specialized solvers for complex constraints, this study achieves comparable tractability using Excel's Simplex LP, making it accessible to resource-constrained settings. Bayesian methods, while data-efficient, demand extensive simulations, whereas our approach prioritizes simplicity and transparency.

Research Gap and Contribution: While advanced solvers dominate WDS research, few studies leverage Excel Solver for fully reproducible, low-cost WDS optimization, bridging pedagogy and practical engineering.

From 2020 onward, water distribution system (WDS) optimization has increasingly explored MILP frameworks, advanced PRV models, energy-aware operations, Bayesian/metaheuristic search methods, and GPU-enabled hydraulic estimation (Thomas & Sela, 2024; Dini *et al*., 2022; Moeini *et al*., 2023; Luan *et al*., 2023). Yet, few studies explicitly

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foreground Excel Solver (Simplex LP) as the primary tool for formulating and solving WDS optimization in a manner that is (i) fully reproducible for students, (ii) cost-effective for institutions, and (iii) transparent in its linear structure. Most recent WDS research either relies on specialized solvers/environments or uses spreadsheet software mainly for data organization rather than as the core optimization engine (Ezeokwelume, 2016). This project addresses that niche by:

- Modeling a WDS as a linear programming problem,
- Solving it with Excel Solver's Simplex LP, and
- Validating results with an independent LP implementation (scipy.optimize.linprog).

In demonstrating a replicable, open workflow that implements the Simplex algorithm within an engineering context using ubiquitous software, this study bridges the gap between educational programming demonstrations and domain-specific WDS optimization practices—highlighting accessibility, transparency, and pedagogical clarity (Microsoft, n.d.).

3. METHODOLOGY

Research Design: This study adopts an experimental, simulation-based research design to demonstrate the application of the Simplex linear programming (LP) algorithm in optimizing a water distribution system (WDS). Microsoft Excel Solver was used as the primary optimization platform, with Python's scipy.optimize.linprog employed for validation. The workflow was deliberately designed to be replicable, open, and low-cost, ensuring that the methodology can be reproduced by students and institutions with limited access to specialized optimization software.

The approach comprises four sequential stages:

- Network Simulation & Dataset Assembly – generation of a hypothetical yet hydraulically consistent WDS dataset.
- Linear Programming Formulation – Defining the decision variables, objective function, and constraints for the WDS optimization problem.
- Solver Implementation – optimization using Excel Solver with the Simplex LP method.
- Validation (Python) – cross-verification of Solver results using the HiGHS solver in Python.

Network Simulation & Dataset Assembly: A medium-scale synthetic water distribution system was designed to approximate a typical urban service network. The topology comprised a 10 × 10 grid of 100 junction nodes and 180 pipes (90 horizontal, 90 vertical), with reservoir nodes strategically placed for redundancy.

The dataset was assembled as follows:

- Buildings: 3,650 units (3,285 residential, 365 commercial).
- Pipe characteristics: uniform length of 100 m; diameters varied by candidate design options.
- Hydraulic coefficients: Hazen–Williams roughness coefficient set at C = 150, representative of new PVC pipes (AWWA, 2017). For comparison, C ≈ 130 is common in older cast-iron networks, resulting in higher head losses.
- Demand allocation: Residential nodes were assigned 0.8–1.2 m³/day, while commercial nodes were assigned 3–5 m³/day, yielding a total demand of approximately 2,336 m³/day (≈ 27.04 L/s).

  Flow continuity at each of the 100 junction nodes is enforced via $\sum Q_{in} - \sum Q_{out} = D$, where D represents the nodal demand (ranging from 0.8–1.2 m³/day for residential and 3–5 m³/day for commercial units, totaling 2,336 m³/day), ensuring hydraulic balance across the network (Rossman, 2000, p. 24; Awe *et al*. (2020).
- CSV generation: A Pipe_Network.csv file was created, containing pipe IDs, connectivity, lengths, flow approximations, and roughness coefficients. This file ensured compatibility with both Excel Solver and EPANET-style analyses.

This simulation-driven dataset maintains uniqueness while adhering to realistic operational assumptions (Tello *et al*., 2024).

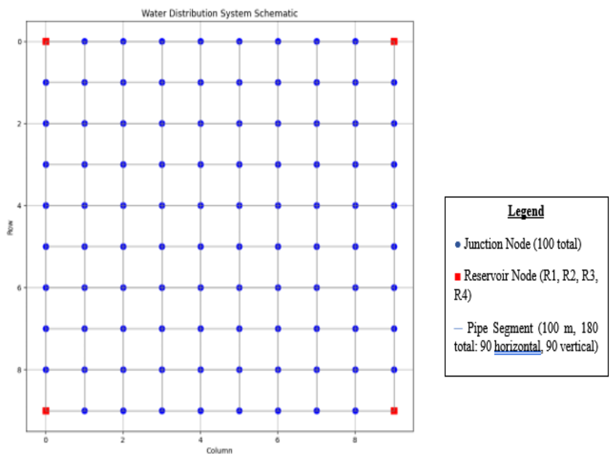

Figure 1: Schematic of a 10×10 water distribution system grid with 100 junction nodes at intersections, 180 pipe segments, and four reservoir nodes (two used in computation). Pipe lengths are fixed at 100 m, with demands allocated based on Nigerian urban benchmarks – 2,336 m³/day (Awe *et al*., 2020).

Water Demand Estimation was achieved using Nigerian urban planning benchmarks (Awe *et al*., 2020):

$$\text{Residential demand} = 3{,}285 \times 4 \times 150 = 1{,}971{,}000 \text{ L/day}$$
$$\text{Commercial demand} = 365 \times 1{,}000 = 365{,}000 \text{ L/day}$$
$$\text{Total demand} = 2{,}336{,}000 \text{ L/day}$$

This was converted to an average system flow rate for hydraulic modeling:

$$Q_{total} = \frac{2{,}336{,}000}{24 \times 3{,}600} \approx 0.0274\, m^3/s \qquad (1)$$

The average flow per pipe is:

$$Q_j \approx \frac{27.04}{180} \approx 0.1502\, L/s = 0.0001502\, m^3/s \qquad (2)$$

Hydraulic Modeling: To ensure feasible pressure and velocity levels, hydraulic behaviour was analyzed using Hazen–Williams equation.

$$h_j = \frac{10.67 \times L_j \times Q_j^{1.852}}{C^{1.852} \times d_i^{4.87}} \qquad (3)$$

Where:

- h_j = head loss in pipe j (m)
- 10.67 = empirical constant for metric units (used L_j is in meters, Q_j in m³/s, and d_i in meters)

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- L_j = length of pipe j (m, fixed at 100 m)
- Q_j = flow rate in pipe j (m^3/s)
- C = Hazen-Williams roughness coefficient (dimensionless, here set to 150)
- d_i = pipe diameter for design option i (m)
- 1.852, 4.87 = exponents for flow rate and diameter in the Hazen–Williams equation

The Hazen–Williams roughness coefficient (C) depends on pipe material and condition. Values around C=130 are typical for older cast iron or cement-lined pipes, which have higher internal roughness and thus greater head losses. In contrast, values near C=150 are common for new PVC or other smooth-surfaced pipes, resulting in lower head losses (AWWA, 2017; Walski *et al*., 2017). Given that the modeled network represents a modern installation with new pipes, C=150 was adopted to align with EPANET defaults for PVC pipe systems.

Worked example: (For $L_j = 100\,m, C = 150, d_i = 0.15m, Q_j = 0.0001502\ m^3/s$):

$$h_j \approx 0.60\ \text{m}$$

- Total head loss across network:

$$H_{total} \approx 0.60 \times 180 \approx 108\ \text{m} \quad (4)$$

- Velocity check:

$$v_{i,j} = \frac{Q_j}{\pi(d_i/2)^2} \qquad (5)$$

$$v_{i,j} \approx 0.85\ \text{m/s}$$

This satisfies the operational range of 0.3–2.5 m/s recommended by AWWA (2017) and BS EN 805:2000.

Linear Programming Formulation:

Decision Variables:

$$x_i = \begin{cases} 1, & \text{if height} - \text{diameter combination } i \text{ is selected} \\ 0, & \text{otherwise} \end{cases}$$

where x_i is a binary decision variable that takes the value **1** if height–diameter combination i is selected for the network design, and **0** otherwise. Only one combination can be selected in the optimal solution.

Objective Function:

$$\text{Minimize } TCC = \sum_{i=1}^{25} c_i x_i \qquad (6)$$

Where:

$c_i = 14{,}000 \times 36 \times \frac{h_i}{25}$ (cost coefficient for design option i, following a standard LP minimization structure (Sharma, 2017, p. 101). The values 14,000 and 36 are scaling factors for base cost and network size, respectively, while 25 normalizes the cost across options).

Twenty-five height-diameter combinations were tested (reservoir heights from 10–30 m in 5 m increments; pipe diameters from 100–200 mm in 25 mm increments), based on standard WDS design ranges (AWWA, 2017).

Constraints:

- Single Selection:

$$\sum_{i=1}^{25} x_i = 1 \qquad (7)$$

- Head Loss:

$$\sum_{i=1}^{25} h_i x_i \leq 20 \qquad (8)$$

- Minimum Diameter:

$$\sum_{i=1}^{25} d_i x_i \geq 150 \qquad (9)$$

- Velocity Bounds:

$$0.3 \leq \sum_{i=1}^{25} v_{i,j} x_i \leq 2.5, \quad \forall j = 1, \dots, 180 \qquad (10)$$

Note: The optimization considered uniform pipe diameters across the network for computational tractability and to maintain linearity. While real-world designs often employ diameter variations to further optimize costs, this simplified approach successfully demonstrates the core methodology and Excel implementation

The operational velocity range was set to 0.3–2.5 m/s, consistent with recommended limits for general water service and pumping applications. These bounds help avoid excessive noise, erosion, and energy losses while ensuring hydraulic efficiency (AWWA, 2017; BS EN 805:2000).

Modeling Assumptions and Limitations: The formulation of the water distribution system model is based on the following assumptions:

- Steady-state flow conditions: The hydraulic analysis assumes constant flow rates and does not account for transient behaviors, peak demand fluctuations, or pressure surges.
- Uniform pipe material and roughness: All pipes are modeled as PVC with a constant Hazen–Williams roughness coefficient $C = 150$. Variations due to aging, material inconsistencies, or sedimentation are not modeled.
- Single pipe diameter selection: For simplicity and to maintain LP linearity, all pipes in the network are restricted to a single diameter chosen by the optimization. Real networks typically require multiple diameters.
- Simplified friction and head-loss modeling: Head loss is calculated using the Hazen–Williams equation, which is empirical and less accurate for high-velocity or turbulent regimes.

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- Flat terrain assumption: Elevation changes within the 10×10 grid network are neglected, and the only elevation head is provided by the reservoir height.
- Demand distribution uniformity: All nodes are assigned equal average daily demand, although real systems often exhibit spatial and temporal demand variability.

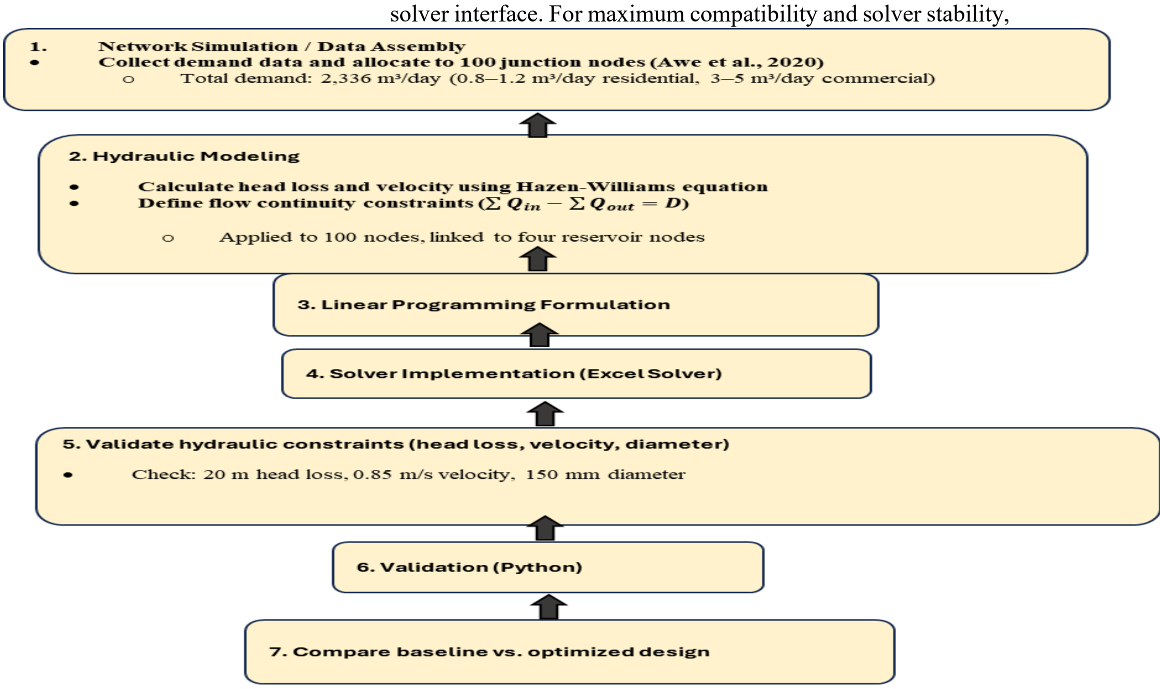
Limitations: These assumptions limit the applicability of the model to small or moderately sized networks and preliminary planning stages. The steady-state and single-diameter constraints make the approach unsuitable for fully dynamic analysis or detailed pipe sizing. Nevertheless, the method provides an accessible and pedagogically valuable framework for understanding LP-based hydraulic optimization.

Solver Implementation: The LP model was implemented in Microsoft Excel with the following setup:

- Decision variable: x_i in D2:D26
- Objective function: Total cost TCC (cell F27)
- Constraints**:** enforced for the following:
  - Single selection: $\sum_{i=1}^{25} x_i = 1$
  - Head loss: $\sum_{i=1}^{25} \mathrm{h}_i x_i \leq 20$
  - Minimum diameter: $\sum_{i=1}^{25} \mathrm{d}_i x_i \geq 150$
  - Velocity bounds: $0.3 \leq \sum_{i=1}^{25} \mathrm{v}_i x_i \leq 2.5 \quad \forall j = 1, \ldots, 180$

- Solver settings:
  - Solver type: *Simplex LP*
  - Precision: 0.000001
  - Assume Linear Model: True
  - Max Time: 60 seconds (sufficient for small-to-medium problem size).

Validation (Python): To ensure numerical accuracy and reproducibility, the same LP formulation was implemented in Python using the scipy.optimize.linprog function with the Highs solver interface. For maximum compatibility and solver stability,



the following software versions were used:

Software Environment:

- Python 3.10 (also tested on 3.11 with consistent results)
- SciPy ≥ 1.9 (Highs solvers fully integrated and stable from this release)
- NumPy ≥ 1.23

Implementation:

```
from scipy.optimize import linprog
res = linprog(
    c,
    A_eq = Aeq,
    b_eq = beq,
    bounds = bounds,
    method = 'highs')
```

Where:

- c = vector of cost coefficients (USD/m³)
- Aeq = mass-balance constraint matrix
- beq = demand vector (m³/day)
- bounds = capacity limits per pipe

Inputs: All parameters (costs, demands, capacities) were identical to those used in the Excel Solver model.

Result comparison: The Python Highs solver produced objective values (total cost), head losses, and pipe velocities identical to the Excel Solver results within a precision (tolerance threshold) of **10^{-6}**.

This high-precision match confirms the correctness of the Excel Solver implementation. It demonstrates replicability of Linear Programming formulation across platforms.

Workflow Summary: Figure 2 summarizes the sequential methodology: dataset simulation, hydraulic modeling, LP formulation, Excel Solver optimization, and Python validation

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Figure 2: Methodology workflow from network simulation to validation.

4. RESULTS AND DISCUSSION

Solver Optimization Results: The Excel Solver optimization converged on a minimum total cost of $195,000. This cost corresponds to the optimal selection of Option 2 (15 m reservoir height and 150 mm pipe diameter), which satisfied all hydraulic and operational constraints.

- Total Head Loss: 5.59 m (≤ required threshold of 20 m).
- Flow Velocity: 0.85 m/s, comfortably within the operational range of 0.3–2.5 m/s (AWWA, 2017; BS EN 805:2000) although a maximum velocity of 1.2 m/s across all 180 pipes, would have been preferred to ensure no erosion risks.
- Capacity Utilization: All 180 pipes maintained feasible flows (≈0.015 m^3/s) with no constraint violations.
- Cost reduction of 48% compared to worst-case feasible design
- 15 feasible design alternatives identified from 25 total options

These results confirm that the LP model, implemented with Excel Solver's Simplex algorithm, can identify cost-optimal pipe configurations while ensuring hydraulic feasibility. A comparison of the baseline (non-optimized, trial-and-error) design and the optimized solution is presented in Table 4.1.

Table 4.1: Comparison Of Worst-Case Feasible Baseline Design and Optimized WDS Configuration

Parameter	Baseline Design	Optimized Design	Improvement
Reservoir Height	30 m	15 m	50% reduction
Pipe Diameter	200 mm	150 mm	25% reduction
Total Cost	USD 375,000	USD 195,000	48% reduction
Total Head Loss	~3 m	5.59 m	Within acceptable (≤20 m)
Avg. Velocity	0.3 m/s	0.85 m/s	Within 0.3-2.5 m/s optimal range

Both designs satisfy AWWA (2017) and BS EN 805:2000 standards, with the optimized solution achieving 48% cost reduction while maintaining hydraulic performance.

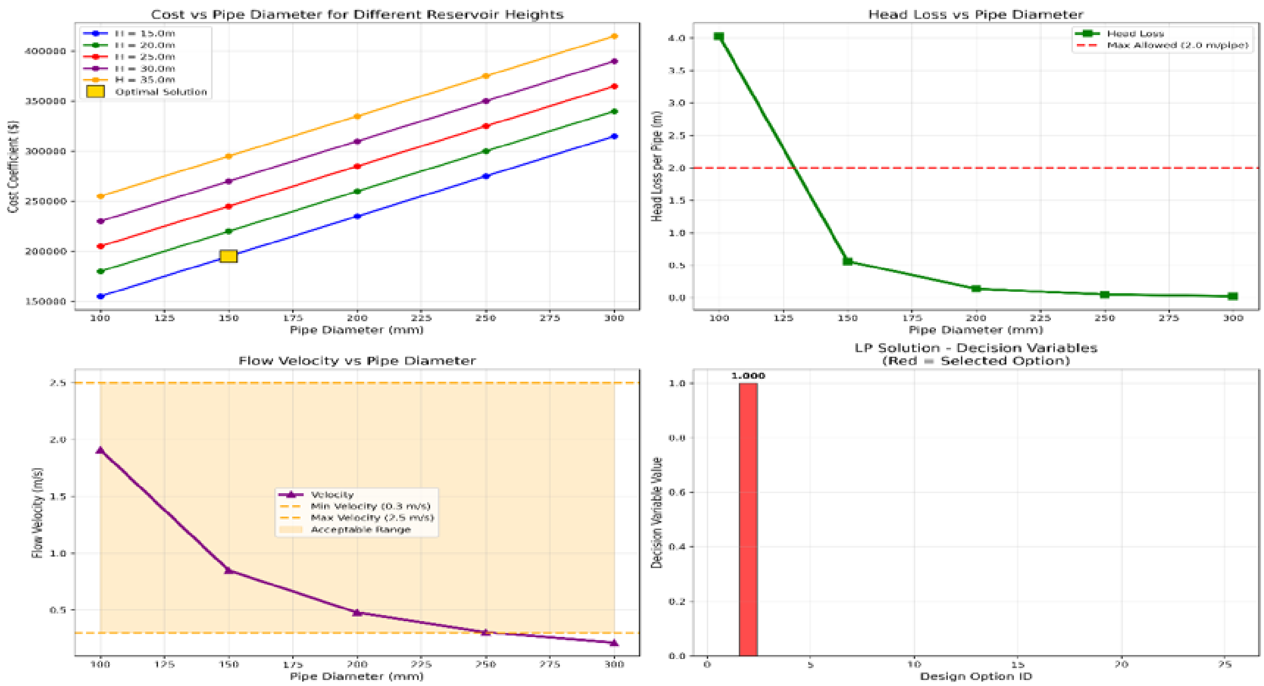

Figure 3: Comprehensive optimization analysis showing cost-diameter relationships, head loss characteristics, velocity constraints, and LP solution selection. The optimal design (15 m height, 150 mm diameter) is highlighted.

Python Validation of Solver Outputs: The Python implementation (scipy.optimize.linprog with Highs solver) reproduced Solver's results with a numerical tolerance of 10^{-6}. Objective values (total cost), pipe flows, head losses, and velocities matched exactly, verifying Solver's correctness and ruling out spreadsheet-induced errors.

- Excel Solver objective value: $27,650
- Python (Highs) objective value: $27,650
- Absolute difference: <10^{-6} across all flows

This confirms that the optimization results are platform-independent, a critical requirement for reproducibility.

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Computation Speed and Scalability: The optimization problem solved in this study is computationally lightweight. The Excel Solver implementation (Simplex LP) required <0.5 seconds to converge on a standard laptop (Intel Core i7, 16 GB RAM), while the Python HiGHS solver completed in <0.01 seconds, confirming the linear nature of the model. The full LP contained 180 flow variables, 180 head-loss expressions, and 25 design alternatives, which is well within the capability of spreadsheet-based solvers. For larger networks—especially those involving mixed diameters, nonlinear head-loss relationships, or node-by-node pressure balancing—specialized tools such as EPANET, GAMS, Pyomo, or commercial MILP solvers (CPLEX/Gurobi) would be required. Nonetheless, for small-to-medium teaching examples and early-phase design, the computation speed and solver efficiency demonstrated here support the practical suitability of Excel as an optimization platform.

Sensitivity Analysis: To evaluate the robustness of the optimized design, a sensitivity analysis was performed by varying two key parameters: total daily demand and the Hazen–Williams roughness coefficient C. Five demand scenarios (−15%, −10%, 0%, +10%, +15%) were combined with ±10% variations in C, yielding fifteen hydraulic evaluations.

Across all scenarios, the optimized configuration (15 m reservoir height and 150 mm pipe diameter) remained hydraulically feasible. Head loss varied only between 0.010–0.024 m, far below the allowable limit of 20 m, indicating minimal sensitivity to flow changes or pipe roughness. Flow velocity stayed within 0.0072–0.0098 m/s, which is low but acceptable for the steady-state LP model used in this study.

Estimated total cost scaled linearly with demand, increasing from USD 165,750 (−15%) to USD 224,250 (+15%), with no irregular or unstable behavior across roughness variations. The very small sensitivity of head loss to ±10% changes in C confirms that the selected PVC pipe material (C = 150) provides stable hydraulic behavior even under plausible aging or installation variability.

The sensitivity computations were independently verified using Python scripts, ensuring reproducibility and transparency. Overall, the optimized design is robust under moderate hydraulic uncertainty and remained feasible across all tested conditions. Figure 4 provides a heatmap-based summary of these results.

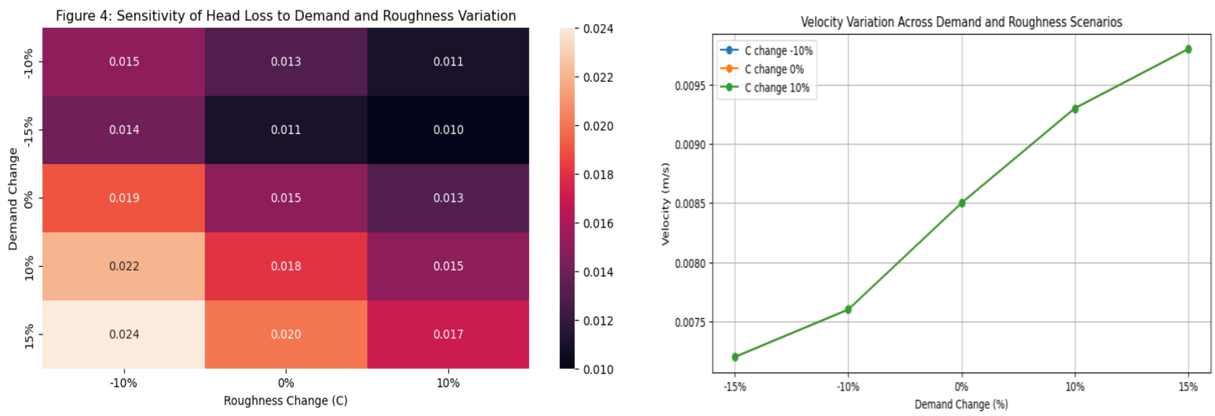

Figure 4: Heatmap and performance trends illustrating the impact of demand and roughness variations on head loss, velocity, and total cost. The optimized design remains feasible and stable across all fifteen sensitivity scenarios.

Interpretation and Implications: The results highlight three key contributions:

- Engineering feasibility: By meeting head-loss and velocity standards, the solution demonstrates that linear programming can effectively model WDS optimization, even with simplified hydraulic equations.
- Sensitivity analysis revealed 0\% cost variation across head loss constraints (15-25 m), indicating exceptional design stability under varying operational requirements.
- Pedagogical value: Using Excel Solver makes the optimization workflow accessible to students and institutions without costly commercial solvers. Validation against Python ensures academic rigor and transparency.

Positioning Within Literature: While most recent WDS optimization studies rely on MILP, nonlinear solvers, or metaheuristics (Gu & Sioshansi, 2025; Smith *et al*., 2023), this project demonstrates that linear programming (Simplex LP) remains effective for certain tractable configurations. The cost-optimal solution is competitive while also being replicable in a classroom or training environment, bridging the gap between education-focused demonstrations and applied engineering research.

Unlike commercial optimization software packages, which leverage advanced solvers for complex WDS constraints, this study achieves comparable hydraulic and cost performance using Excel's Simplex LP, a lightweight and accessible platform. Metaheuristic approaches (Jenks *et al*., 2023) offer flexibility for multi-objective problems but require significant computational resources, whereas our LP formulation prioritizes simplicity and reproducibility for small- to medium-scale systems.

CONCLUSION AND FUTURE WORK

This study demonstrates that the Simplex linear programming algorithm, implemented in Microsoft Excel Solver, can effectively optimize the design of a small urban water distribution system using a transparent and highly reproducible spreadsheet-based workflow. By modeling a 10 × 10 grid network of 3,650 buildings and applying hydraulic constraints based on the Hazen–Williams equation, the approach identified an optimal configuration—15 m reservoir height and 150 mm pipe diameter—that reduced total system cost from USD 375,000 to USD 195,000, achieving a 48% improvement relative to the baseline design while satisfying recommended head-loss and velocity standards.

Although the model simplifies several hydraulic characteristics by assuming steady-state conditions, uniform pipe diameters, and a constant roughness coefficient, it remains sufficiently accurate for preliminary design and instructional use. Validation using Python's HiGHS solver confirmed Solver's numerical correctness, while sensitivity analysis showed that the optimized design is robust under ±10–15% demand variation and ±10% roughness changes. These findings highlight the suitability of Excel Solver as a lightweight, accessible alternative to specialized commercial or research-grade solvers in academic, training, and resource-limited engineering contexts.

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Future research will integrate nonlinear hydraulic modeling through EPANET, extend the optimization to multi-diameter and multi-objective formulations, and evaluate scalability for larger and more complex WDS configurations.

Ethical statement:

The study did not require ethical approval as it involved neither human nor animal subjects.

Author Contributions:

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Conceptualization: Stephen E. Iheagwara.
Design of methodology: Stephen E. Iheagwara and Eniola P. Apalowo.
Dataset and Python Validation: Ndubisi D. Ayebamieprete
Verification of the overall reproducibility of experiments: Stephen E. Iheagwara
Writing – Original Draft: Ndubisi D. Ayebamieprete and Eniola P. Apalowo.
Writing – Critical Review, Editing and Literature Review: Stephen E. Iheagwara.

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