

# The Impact of Dripline Parameters on Water Travel Time: A Predictive Modeling Study for Precision Irrigation

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## Abstract

Accurate prediction of water travel time in drip irrigation systems is essential for efficient water and nutrient delivery. This study develops a predictive model for travel time by discretizing the dripline into segments and calculating the advance time within each segment based on established hydraulic principles. Using Python 3.12, we implemented a model that relates travel time to key dripline parameters: emitter flow rate, dripline diameter, and segment length. A total of 1,536 combinations of parameters were simulated to train and evaluate the model. Optimization techniques from SciPy, including a suite of algorithms such as SLSQP, BFGS, Nelder-Mead, Powell, TNC, and COBYLA, were used to calibrate the model parameters against target travel times. SLSQP and BFGS showed the best performance, achieving  $R^2$  values of 0.99 and RMSE values of approximately 14.05 minutes. A field trial was conducted to validate the model using measured versus calculated travel times, showing high agreement between observed and predicted values. Our analysis reveals the significant influence of dripper flow rate on travel time, followed by dripline diameter and segment length. It was also found that 95% of the dripline length is traversed in only 50% of the total travel time, indicating a non-linear advance dynamic. This research demonstrates the effectiveness of optimization methods for accurately predicting travel time in drip irrigation systems, contributing to improved irrigation scheduling and more precise resource applications.

## Keywords

Drip Irrigation, Hydraulic Simulation, Travel Time

## 1. Introduction

Precise control over water and nutrient delivery is essential for maximizing crop yields and minimizing resource waste in modern agriculture [1]-[3]. Accurate calculation of water travel time within a drip irrigation system is a critical component of achieving this control [4]. In fertigation, understanding the duration required for water to traverse the irrigation system before exiting through the dripper and reaching the soil is crucial during irrigation processes, as it directly impacts the precision of water and nutrient management. Accurate knowledge of travel time enables informed decisions, enhancing the accuracy of water and nutrient delivery [5] [6].

Traditional methods for estimating travel time in drip irrigation systems often rely on simplified assumptions that do not account for the variable flow dynamics caused by emitter discharge along the lateral [7]. These simplifications can lead to significant inaccuracies, particularly in systems with long pipelines, heterogeneous slopes, or variable emitter spacing. As precision agriculture increasingly depends on fine-scale temporal and spatial control, the need for robust, adaptable, and computationally efficient models becomes more pressing [8]. Developing predictive tools that integrate hydraulic theory with optimization techniques allows for a more accurate and scalable estimation of travel time, ultimately supporting more effective fertigation strategies and sustainable resource use [9]. The travel time calculation process typically involves three key steps: the first one involves calculating the travel time in the mainlines, which are the primary conduits carrying water throughout the system, the second one is focus on determining the travel time through the manifold, which distributes water to various branches of the system and finally, the third step involves assessing the travel time in the dripline, which directly delivers water to the plants or soil [4].

The calculation relies on fundamental hydraulic equations, particularly the general flow Equation. This equation establishes a relationship between fluid velocity, pipe cross-section, and the volume of water passing through the pipe [4] [10] [11].

$$\text{velocity} = \text{flow} \cdot \text{area}^{-1} \quad (1)$$

$$\text{travel}_{\text{time}} = \text{distance} \cdot \text{velocity}^{-1} \quad (2)$$

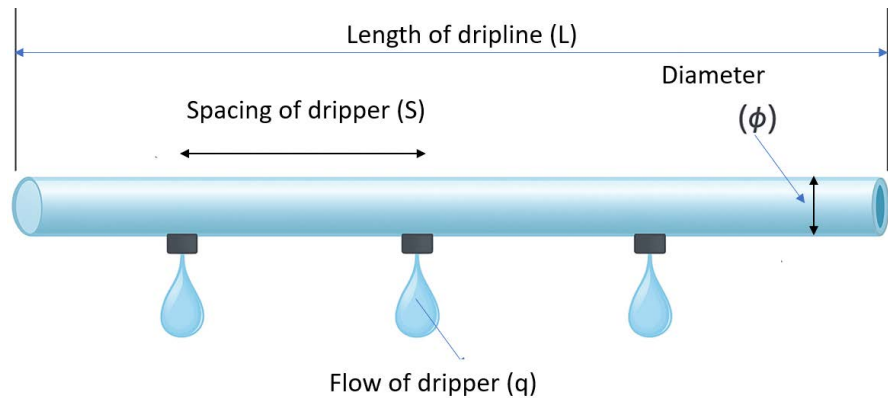
These equations are straightforward to solve in a non-complex pipe system where the inflow matches the outflow. However, in irrigation pipes, as illustrated in **Figure 1**, the flow consists of a combination of dripper properties, pressure variations, and their quantities. As a result, the total flow within the pipe experiences a consistent and gradual decrease along the hose's length, leading to a corresponding decrease in velocity [12]. Consequently, the methodology for calculating travel time must be adapted, involving the summation of individual travel times for each segment.

In situations where multiple drippers are present, as commonly seen in drip lines, determining the travel time involves first establishing partial velocities ( $v_i$ ) for each distance along the drip line. Subsequently, using these partial velocities,

the partial travel time can be calculated [12]:

$$\text{travel}_{\text{time}} = \sum_{i=1}^n \frac{S}{v_i}; \quad v_i = \frac{4 \cdot q \cdot n_i}{\pi \cdot \phi^2} \quad (3)$$

where  $S$  is the spacing between drippers,  $q$  is the drip flow,  $n$  is the number of drippers in the hose, and finally  $\phi$  is the hose's diameter.



**Figure 1.** Diagram to describe the flow in irrigation driplines.

It presents a valuable opportunity for obtaining accurate travel time estimations in auto-compensated drip lines, where there is minimal variance in flow across a range of pressures. In contrast, for non-pressure-compensating driplines, the emitter flow rate is directly dependent on the pressure within the hose ( $P$ ), following Torricelli's Law [13] [14]. Specifically, these driplines exhibit a flow exponent ( $x$ ) of approximately 0.45, whereas pressure-compensating driplines have an exponent of 0, indicating a constant flow regardless of pressure fluctuations [12] [13].

However, the manual calculation of travel time, involving intricate data organization and numerous individual computations, is not only arduous but also lacks the depth of analysis required for optimizing system performance. This study tackles this issue by analyzing the travel time dynamics in a dripline and exploring the potential for developing a novel equation that accurately describes the behavior of this variable. Such an equation would be invaluable in optimizing fertigation practices, enabling more precise delivery of both water and nutrients [6] [15]. By investigating the dynamics of water flow and distribution within the dripline, this study aims to provide valuable insights and recommendations for enhancing the efficiency and effectiveness of fertigation systems.

This study leverages the *scipy.optimize.minimize* function [16], a mix of gradient-based and gradient-free algorithms, this powerful tool within the SciPy library in Python [17], to address the challenge of travel time prediction. This function provides a unified interface to a variety of optimization algorithms, enabling the minimization of a scalar function of one or more variables [18]. In our context, this function is crucial for optimizing the parameters of a physical model representing the drip irrigation system. Specifically, we formulate the travel time pre-

diction as a mathematical minimization problem.

The core of this problem lies in defining an appropriate objective function that quantifies the difference between observed or desired travel times and those predicted by a hydraulic model. This objective function is typically a function of several key design and operational parameters of the drip irrigation system, including flow rate ( $q$ ), dripper spacing ( $S$ ), dripline length ( $L$ ), and dripline diameter ( $\varnothing$ ). The hydraulic model itself may be based on established hydraulic principles or empirical relationships, or a combination thereof.

The objective function is constructed to minimize the difference between the calculated travel time (derived from the hydraulic equations and dependent on  $Q$ ,  $S$ ,  $L$ , and  $\varnothing$ ) and a target or observed travel time. This minimization process is facilitated by `scipy.optimize.minimize`, which allows for the determination of the optimal relationship between the design parameters and the resulting travel time [18] [19].

The function provides several optimization methods, including gradient-based approaches (e.g., BFGS, Newton-CG, L-BFGS-B) and gradient-free algorithms (e.g., Nelder-Mead, Powell), each suitable for different problem characteristics. The selection of the method depends on factors such as the availability of gradient information, the smoothness and convexity of the objective function, and computational cost [17] [20].

By minimizing the objective function, we can fine-tune the system's design, ensuring more uniform water distribution, reducing water waste, and improving overall irrigation efficiency. This optimized model can then be used for predictive purposes, enabling better management of irrigation scheduling and resource allocation.

Through meticulous analysis and data experimentation, this research endeavors to refine our understanding of how water travels through driplines, contributing to advancements in agricultural irrigation techniques [6] [15]. This paper aims to delve into the interplay among emitter flow rate, distance, length, and diameter of drip lines concerning lead time calculation. Additionally, it proposes a streamlined approach utilizing hydraulic simulations via Python and optimization algorithms to obtain these insights effortlessly.

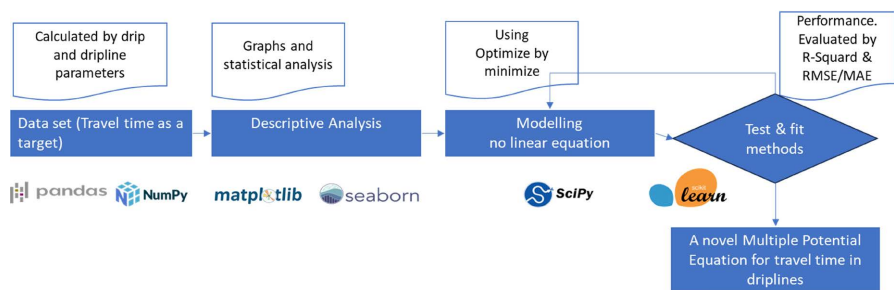
## 2. Resource and Methods

This project was undertaken using Python 3.12 [21]. With the Jupyter notebook [22], we established an Interactive Development Environment (IDE) for constructing models and executing algorithms for predictive analysis. The development of datasets and their processing aspect was facilitated by the Pandas [23] and NumPy libraries [24], offering robust capabilities for organizing and cleaning data. Graphical representations and data analyses were facilitated using the Matplotlib [25] and Seaborn libraries [26]; while modelling and evaluating model algorithms were executed within the scikit-learn environment [27] and SciPy. The integration of these tools and processes was seamlessly achieved through the E-

Notebook. The process was performed on the IDE as shown in **Figure 2**.

## 2.1. Dataset

The project involved the development of an algorithm to calculate travel times for each segment of the drip line using partial velocities derived from Formulas (3) - (4). The program utilized inputs such as flow rate (l/h), distance between drippers (m), hose diameter (mm), and hose length (m), as detailed in **Table 1**. These inputs were processed through iterative loops to calculate travel times for each distance between water outlets.



**Figure 2.** Python environment and project road map.

A significant challenge encountered during the project was the need to program multiple loops to generate a comprehensive dataset. This dataset needed to cover a wide range of parameters to ensure accuracy in lead time predictions. Specifically, the dataset included eight flow rate variations ranging from 0.4 to 3.5 l/h, distances between drippers ranging from 0.2 to 0.9 meters with 0.1 m increments, and hose lengths varying from typical applications from smallholder to large-scale projects (ranging from 20 to 300 m). Additionally, hose diameters of polyethylene 13 mm, 16 mm, and 20 mm, which are commonly used in performance settings, were considered. **Table 1** provides a detailed overview of the inputs utilized for simulation.

**Table 1.** Inputs for simulation of the advance time, using the parameters of the drip irrigation hose [13].

Dripper Parameter			Dripline Parameter
Flow (l/h)	Spacing (m)	Length (m)	Diameter (mm)
0.4	0.2	20	
0.6	0.3	40	
0.8	0.4	80	13.6 (Heavy Wall Dripline)
1.0	0.5	120	16.2 (Thin & Medium Wall Dripline)
1.6	0.6	160	22.2 (Thin & Medium Wall Dripline)
2.3	0.7	200	
3.0	0.8	250	
3.5	0.9	300	

The core of this study relies on a comprehensive dataset generated through a hydraulic simulation algorithm. This algorithm, implemented in Python [21] and made publicly available in a Zenodo repository, systematically explores a wide range of drip irrigation system configurations. The full source code of the simulation script is provided in the Data Availability Statement to this paper and in the repository, and is available on Zenodo [28].

A total of 1,536 simulations were carried out, combining different levels of emitter flow rate, emitter spacing, lateral length, and pipe diameter, as summarized in **Table 1**. These values were carefully defined based on commercial drip tape and tubing products widely used in agricultural applications. This ensured that the simulated scenarios remained within the manufacturers' recommended operating ranges, thereby guaranteeing that the resulting hydraulic designs would maintain adequate application uniformity, with a uniformity coefficient (CU) equal to or greater than 85%, in accordance with international precision irrigation standards [13].

For each unique combination of these parameters, the algorithm performs a detailed hydraulic calculation along the dripline lateral. It discretizes the lateral into segments corresponding to the emitter spacing and calculates the flow rate, water velocity, and consequently, the travel time within each segment. This iterative process generates various alternative solutions for water travel time corresponding to each specific combination of factors. Upon completion, the 1,536 unique hydraulic simulation outcomes were obtained, precisely matching the quantity of combinations explored. The resulting dataset, stored as a Pandas DataFrame (*df in the code*), included two critical travel time metrics: one calculated for the entire length of the pipe (*travel\_time*) and another specifically for 95% of the pipe's length (*travel\_time\_95*). This comprehensive dataset was subsequently utilized to test and train the predictive model presented in this paper. Further detailed explanation of the hydraulic calculations, including specific formulas for velocity and travel time, will be available in the Data Availability Statement.

A comprehensive suite of graphical tools was employed for exploratory data analysis to elucidate the relationships between dripline parameters and water travel time. These visualizations, including histograms, scatter plots, and variograms, alongside statistical summaries, served as the primary means of analyzing and characterizing the behavior of travel time within the drip irrigation system. Specifically, histograms provided insights into the distribution of travel times, revealing potential skewness or multi-modal patterns. Scatter plots explored correlations between travel time and individual dripline parameters (e.g., flow rate, dripper spacing, dripline length, and diameter), allowing for the identification of potential linear or non-linear relationships. Variograms were used to investigate the spatial or temporal dependence of travel time, quantifying the degree of correlation between travel times at different locations or times within the system. These graphical and statistical tools, taken together, provided a robust foundation for understanding the complex interplay between dripline characteristics and water travel time [20] [29].

## 2.2. Modelling

To model the complex, non-linear relationship between travel time and the various dripline parameters, a multiple potential equation approach was adopted [29]. This type of equation allows for the expression of the dependent variable (travel time) as a sum of terms, where each term is a product of a coefficient and one or more independent variables (dripline parameters) raised to certain powers. This flexibility is crucial for capturing the intricate interactions between factors like flow rate, dripper spacing, dripline length, and diameter, which are unlikely to be adequately represented by a simple linear equation. Specifically, the form of the multiple potential equation allows for the exploration of power-law relationships, which are common in hydraulic systems. To determine the optimal coefficients and exponents within the multiple potential equations, the *scipy.optimize.minimize* function in Python was employed [17].

$$\text{Travel}_{\text{time}}(T) = A \cdot q^B \cdot S^C \cdot L^D \cdot \emptyset^E \quad (4)$$

**Function Definition:** The core of the optimization process was the definition of an objective function. This function quantifies the discrepancy between the travel times predicted by the hydraulic model ( $T(q, S, L, \emptyset)$ ) and a set of target travel times ( $\text{Travel}_{\text{time}}$ ). The target travel times were determined based on specific irrigation requirements and system design criteria. In this study, the objective function was defined as the sum of squared differences between the predicted and target travel times [17] [18] [30].

$$\text{objective Function} = \sum [T(q, S, L, \emptyset) - T_{\text{Travel time}}]^2 \quad (5)$$

This formulation aims to minimize the overall difference between the model's predictions and the desired travel times. Optimization by *scipy.optimize.minimize* function in Python was used to minimize the defined objective function [18]. This function provides access to a range of optimization algorithms, allowing for flexibility in addressing the specific characteristics of the problem. The optimization process involved iteratively adjusting the dripline parameters ( $q, S, L, \emptyset$ ) to minimize the objective function.

Initial guesses for these parameters were provided to initiate the optimization process. Crucially, all available optimization methods within *scipy.optimize.minimize* were systematically tested, including both gradient-based methods (BFGS, Newton-CG, L-BFGS-B, CG, dogbox, trust-constr, trust-exact, trust-krylov) and gradient-free methods (Nelder-Mead, Powell, COBYLA, SLSQP) [17]. This comprehensive test aimed to identify the most suitable algorithm for this specific application, considering factors like convergence speed, accuracy, and robustness. Constraints were imposed on the parameters to reflect physical limitations [30]. For instance, the dripline diameter and flow rate were constrained to positive values within realistic ranges for typical drip irrigation systems. The dripper spacing and dripline length were also subject to appropriate constraints (Table 1).

### 2.3. Model Evaluation

A rigorous evaluation of the optimized model's predictive accuracy was conducted by comparing its predicted travel times with the pre-defined target travel times. This comparison was performed using both quantitative statistical measures and qualitative visual inspection.

The primary quantitative metrics employed were the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R-squared). The RMSE, calculated as the square root of the squared differences between predicted and target travel times, provided a measure of the average magnitude of prediction errors. MAE is the average of the absolute differences between the predicted values and the actual values. Both a lower RMSE/MAE value indicates better agreement between predicted and target values, signifying higher accuracy [31]-[33].

$$\text{RMSE} = \sqrt{\frac{\sum (y_i - \bar{y}_i)^2}{n}} \quad (6)$$

$$\text{MAE} = \frac{\sum |y_i - \bar{y}_i|}{n} \quad (7)$$

The R-squared, on the other hand, assessed the proportion of variance in the target travel times that was explained by the model. A R-squared value closer to 1 indicates a better fit, implying that the model effectively captures the underlying relationship between dripline parameters and travel time [32] [34] [35].

$$R^2 = \frac{\sum (y_i - p_i)^2}{\sum (y_i - \bar{y}_i)^2} \quad (8)$$

where  $y_i$  are the values that the target variable takes,  $p_i$  are the prediction values,  $\bar{y}_i$  is the average value of the values taken by the target variable, and  $n$  is the number of observations.

Beyond these statistical metrics, a crucial component of the evaluation involved a qualitative assessment of the model's performance through visual inspection. Scatter plots were generated, plotting the predicted travel times against the corresponding target travel times. These visualizations allowed for a detailed examination of the model's predictive behavior across the range of target values. Deviations from the ideal 1:1 line (where predicted values perfectly match target values) were scrutinized to identify any systematic biases or regions of poor prediction accuracy. This visual inspection complemented the quantitative metrics, providing a more nuanced understanding of the model's strengths and limitations [18] [20].

### 2.4. Field Test

To validate the robustness of the proposed equation, a dataset of measured field values was obtained from experimental tests conducted under controlled operational conditions. These tests systematically varied the evaluated parameters: drip-

per spacing (0.25, 0.30, 0.40, and 0.50 m), dripper flow rates (0.8, 1.0, 1.6, and 2.3 L/h), and dripline lengths (25, 50, 100, and 150 m). In all cases, a hose with an internal diameter of 13.6 mm was used to represent the entire domain of the theoretical model.

The model's predictive performance was assessed through regression analysis, comparing the equation's predicted values with the measured field data. The experimental determination of travel time was carried out by injecting fertigation into the hose and recording the moment at which a change in the electrical conductivity was detected at the dripper outlet. During each test, the travel time corresponding to 95% of the hose length and the total travel time along the entire hose were measured.

Model performance was quantified using the coefficient of determination ( $R^2$ ), which indicates the proportion of variance in the field data explained by the model. Additionally, the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) were calculated to evaluate the magnitude and distribution of the prediction errors (in minutes).

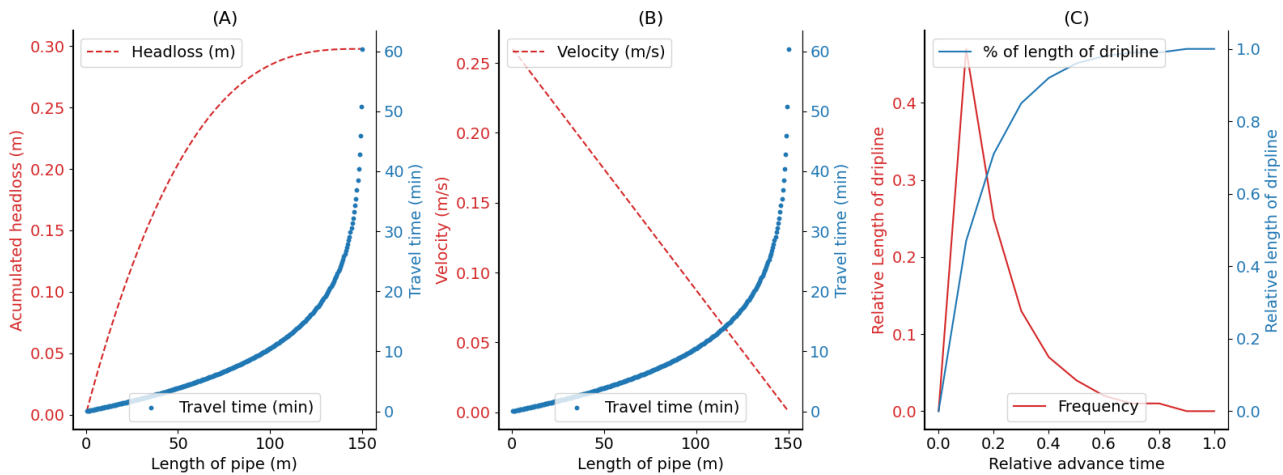
### 3. Results & Discussion

#### 3.1. Behavior of the Travel Time

The travel time results between drippers in drip irrigation lines exhibit exponential growth (**Figure 3(B)**) due to the rapid decrease in velocity, caused by the flow delivered by the dripper along the pipe. This relationship is inverse, indicating that the travel time is inversely proportional to the velocity. As water nears the end of the dripline, its velocity decreases markedly. **Figure 3(A)** further illustrates the inverse relationship with accumulated pressure head loss. The reduction in velocity results in a decrease in pressure drop between the drippers along the pipe, which ultimately contributes to maintaining the flow balance and precision of the irrigation process. Both graphs demonstrate how the decreasing flow in the driplines affects the travel time of water and nutrients in driplines [6] [15].

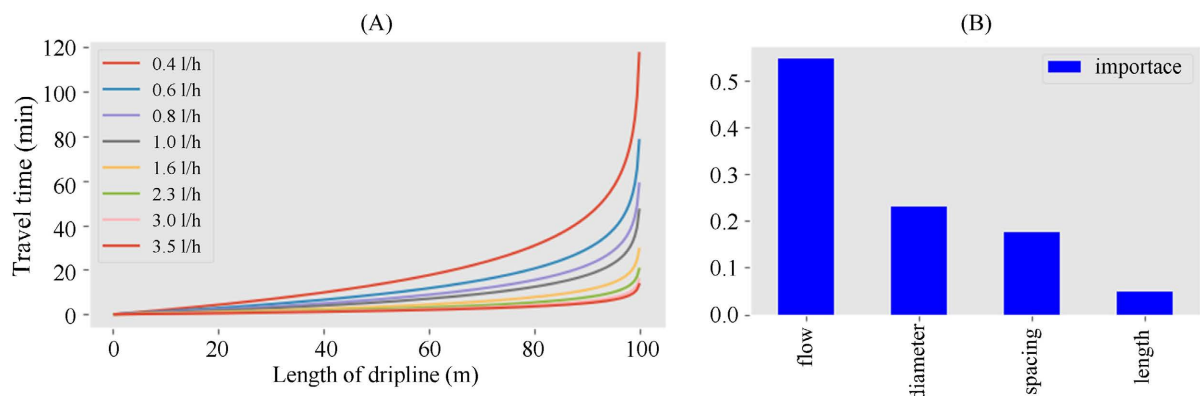
An additional noteworthy observation is depicted in **Figure 3(C)**, which shows the relative travel time versus the relative length of the dripline. The graph indicates a favorable lead time in a shorter time span, particularly noticeable towards the left side. Practically, this suggests that if the water covers 95% of the length, it will have advanced 50% of the total time. This statistic is remarkable: the furthest 5% of the drip line requires 50% of the remaining lead time. Moving forward, this document will focus on deriving equations for calculating travel time for both the total length of driplines and 95% of their length.

This observation underscores a rule of thumb: halving the flow rate of the dripper may result in a doubling of travel time in driplines [9] [12]. This insight is crucial for making informed decisions during project planning and management.



**Figure 3.** Hydraulic behaviour in dripline: (A) shows the relationship between the accumulated head loss versus the distance in the irrigation dripline; (B) shows the decreasing velocity along the pipe; (C) shows the relative percent of length of dripline which responds to the relative advance time.

Based on the influence of variables in calculating travel time using the decision tree regression model, as shown in **Figure 4(B)**, the flow rate emerges as the most influential factor, accounting for over 56% of the variance in lead time. In comparison, variables such as diameter and distance each contribute just under 18%. Notably, opting for a lower flow rate leads to an increase in lead time, highlighting an important consideration for project planning (**Figure 4(A)**).

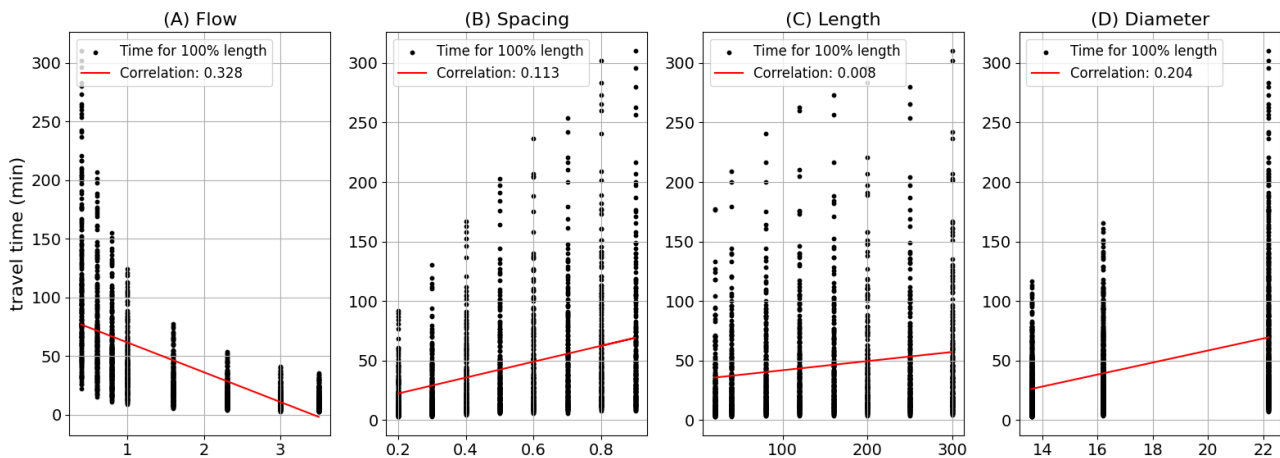


**Figure 4.** Effect of the flow on travel time: (A) travel time differences for various dripper flow rates; (B) shows the importance of ranking features to predict the travel times in driplines.

In search of relationships as an exploratory analysis, several interpretive plots were made, starting with a pair plot in which the interaction of the variables flow, distance, length, and diameter with travel time was established. There is a relationship especially with the flow emitter, where its rate of increase is inversely proportional to the travel time with an  $R^2$  close to 0.32 (**Figure 5(A)**); the spacing between emitter and diameter have a proportional relationship with the travel time of water, its  $R^2$  was less than the correction of flow but greater than the links of length (**Figure 5(B)** and **Figure 5(D)**), the worse return of length makes sense

because it directly affects the amount eventually dropper and with the total flow, becoming a recurrent input (**Figure 5(C)**).

Based on the graph, it appears feasible to develop a regression model among the variables, particularly focusing on the flow rate, diameter, and spacing of the dripper. However, the variable length does not seem to exhibit a strong correlation with any of the feature regressors.

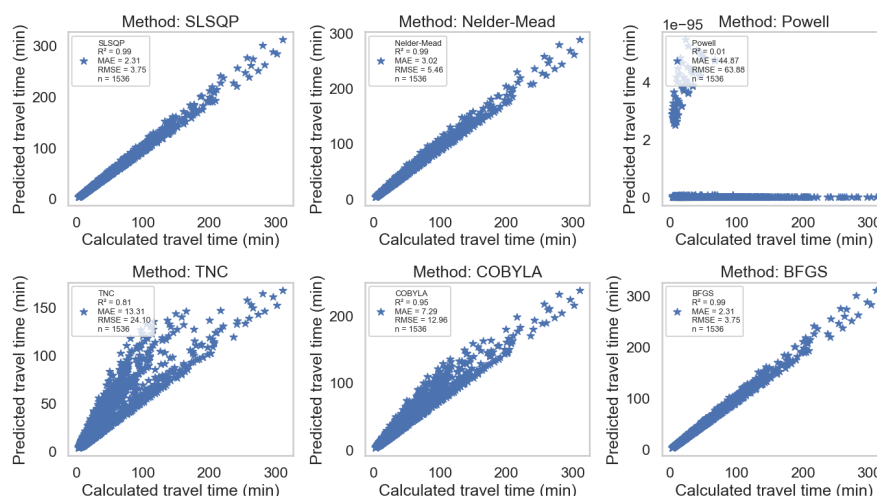


**Figure 5.** Influence of dripline parameters on water travel time: (A) effect of dripper flow rate; (B) response to emitter spacing; (C) (D) relationship with lateral length and pipe diameter, respectively. Each subplot illustrates the calculated travel time for both 100% and 95% of the dripline length, along with the correlation of the simulated data.

### 3.2. Predictive Model for Travel Time

A clear trend emerged from comparative analysis, showing that the predictive performance of the travel time model was highly sensitive to the choice of minimization algorithm and its corresponding hyperparameters. Certain combinations consistently outperformed others, reinforcing the relevance of selecting appropriate optimization strategies to enhance the reliability of the predictions [34] [36].

The results, visualized in scatter plots of predicted versus calculated travel times (**Figure 6**), reveal a significant variation in model performance across different optimization algorithms. SLSQP and BFGS demonstrate the strongest agreement between predicted and calculated values, evident in the tight clustering of points along the 1:1 diagonal line and reflected in their high R-squared values of 0.9933. COBYLA also exhibits a relatively good fit, though with slightly more dispersion and a lower R-squared of 0.9441. TNC shows a moderate correlation (R-squared of 0.8114), but with increased scatter compared to SLSQP and BFGS. In contrast, Nelder-Mead and Powell show considerably weaker correlations, with R-squared values of 0.7619 and 0.0117, respectively, indicating these methods struggled to effectively optimize the model parameters for accurate travel time prediction. The distinct performance of each algorithm underscores the importance of optimization method selection in achieving accurate and reliable model prediction [36]-[38].



**Figure 6.** Results between the calculated travel time vs. the predicted travel time by the different minimization function methods.

A comprehensive presentation of the optimized parameters for the multiple potential equations is provided in **Table 2**. This table details the fitted mathematical constants for each equation, alongside key evaluation metrics, namely the R-squared value and the Root Mean Squared Error (RMSE). These metrics offer a quantitative assessment of the model's performance, with R-squared indicating the proportion of variance in the target variable explained by the model, and RMSE quantifying the average difference between predicted and observed values [31] [32]. The inclusion of both the optimized parameters and these evaluation metrics in **Table 2** allows for a thorough understanding of the model's behavior and its predictive capabilities.

**Table 2.** Parameters for the multiple potential equations and the evaluation indicators for different minimization methods.

Method	A	B	C	D	E	R <sup>2</sup>	RMSE	MAE
SLSQP	0.091	-1.000	0.782	0.193	1.999	0.993	14.053	2.314
BFGS	0.091	-1.000	0.782	0.193	2.000	0.993	14.053	2.314
COBYLA	1.228	-1.004	0.807	0.143	1.157	0.944	187.862	3.023
TNC	10.028	-1.012	0.809	0.099	0.459	0.811	557.481	7.648
Nelder-Mead	1.390	-0.742	1.345	0.382	0.739	0.762	749.516	13.131
Powell	9.749	-0.292	-0.097	-52.77	-23.607	0.012	4080.896	44.875

Beyond the visual agreement observed in the scatter plots, the fitted parameters of the multiple potential equations and their corresponding RMSE values provide further insight into the behavior of each optimization method. Both SLSQP and BFGS converged to identical parameter sets and showed the lowest error values (RMSE  $\approx$  14.05), confirming their numerical stability and capacity to reproduce travel time dynamics accurately. COBYLA delivered acceptable results with moderate error (RMSE = 187.86) and parameter shifts, while TNC showed a noticeable

loss in precision (RMSE = 557.48). More pronounced divergence was observed in Nelder-Mead and especially Powell, which produced unstable or unrealistic parameter estimates, consistent with their poor  $R^2$  values.

Analysis of the experimental data yielded a highly accurate predictive equation, demonstrating a strong fit with a coefficient of determination (R-squared) of 0.9933. This high R-squared value signifies that the equation effectively captures the variability in the observed data, validating its use for precise travel time prediction. Beyond their theoretical value in elucidating the underlying hydraulic dynamics, this equation offers practical utility. Their straightforward mathematical form allows for easy implementation within spreadsheet software, facilitating rapid and accessible calculation of advance times for diverse drip irrigation scenarios. This accessibility enhances the practical applicability of our findings, empowering irrigation managers with a user-friendly tool for optimizing water delivery.

$$\text{traveltime}_{\text{full\_dripline}} = 0.0912 \cdot \frac{\text{spacing}^{0.7824} \cdot \text{length}^{0.1928} \cdot \text{diameter}^2}{\text{flow}_{\text{dripper}}} \quad (9)$$

$$\text{travel time}_{95\% \text{ of Length}} = \frac{\text{travel time}_{\text{full\_dripline}}}{2} \quad (10)$$

The properties of the dripline include its length (measured in meters) and diameter (measured in millimeters), while the spacing between drippers (measured in meters) and the flow rate (measured in l/h) of each dripper are considered dripper-specific properties. By considering these variables, we were able to derive the travel time equation.

The obtained exponents reflect underlying hydraulic relationships, allowing for their direct physical interpretation. The exponent associated with the emitter flow rate of  $(-1)$  is consistent with the basic velocity equation in pressurized pipes, where flow velocity is directly proportional to discharge and inversely proportional to the cross-sectional area. This inherently implies that travel time is inversely proportional to the flow rate, confirming the rule-of-thumb observation that higher discharge leads to shorter travel times.

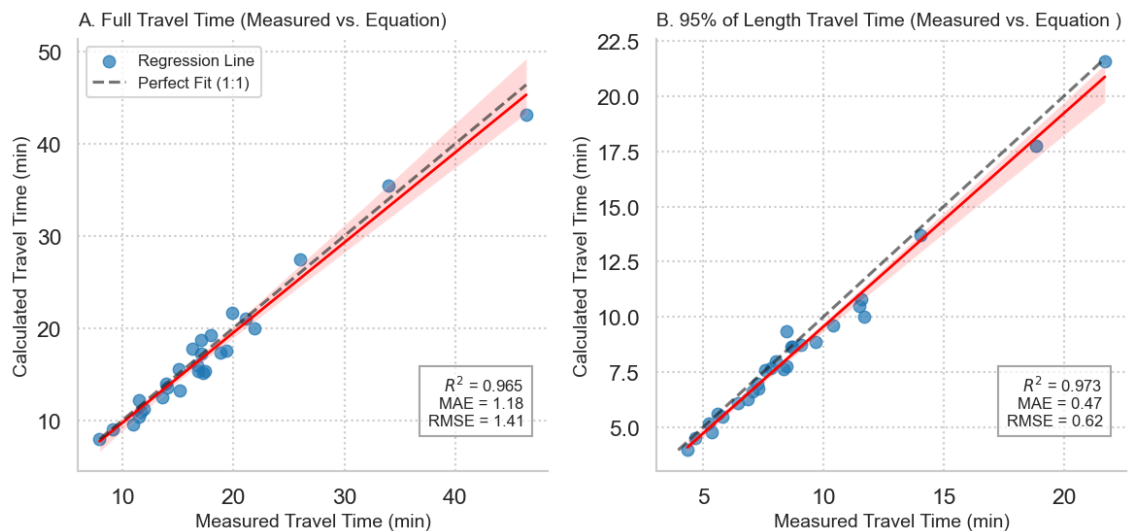
The exponent for lateral length ( $L = 0.1928$ ) indicates a sublinear relationship between length and travel time. This suggests that while an increase in pipe length contributes to an increase in travel time, its effect is less pronounced compared to other variables.

Regarding the exponent associated with pipe diameter ( $D = 2$ ), its physical interpretation aligns with fundamental principles of flow hydraulics in pressurized pipes under constant flow conditions. According to the equation for mean velocity in a circular cross-section,  $v = Q/A = 4Q/(\pi D^2)$ , an increase in diameter reduces the flow velocity, thereby increasing the time required for water to cover a given distance. This generates a direct proportional relationship between travel time and the square of the diameter, which is consistent with the empirical exponent found in the model. While this behavior represents an ideal condition (without considering effects such as pressure losses, friction, or pressure gradients), it is useful for

the initial design of systems as it reflects the impact of diameter on volumetric capacity and flow velocity. Furthermore, this interpretation has been recognized in classic technical literature, such as Keller and Karmeli (1974), who noted that under steady-state conditions and constant flow, diameter exerts dominant control over velocity and, consequently, over filling time of lateral lines [39].

### 3.3. Model Validation Against Field Data

The predictive accuracy of the proposed equation for estimating travel time was validated using field-measured data obtained under controlled experimental conditions. As shown in **Figure 7**, the predicted values closely matched the observed data, indicating that the equation effectively represents the hydraulic behavior of the dripline system. The full travel time (**Figure 7(A)**) exhibited a strong linear relationship between measured and predicted values, with an  $R^2$  of 0.965, confirming that 96% of the field variability was explained by the model. Similarly, the validation for the 95% travel distance (**Figure 7(B)**) demonstrated excellent agreement between predicted and observed results. The regression line nearly overlapped the 1:1 reference line, and the model achieved an even higher coefficient of determination ( $R^2 = 0.973$ ). The associated errors were minimal (MAE = 0.47 min; RMSE = 0.62 min), reinforcing the equation's precision and stability under varying operational conditions.



**Figure 7.** Results between measured travel time tested at the field vs. the predicted travel time by the generated equation: (A) represents the travel time for the total length of the hose; (B) is for 95% of the length.

The consistently high  $R^2$  values and low error metrics across both validation domains confirm that the developed equation is a robust and reliable predictive tool for estimating travel time in drip irrigation systems. These results highlight its potential applicability in system design, fertigation management, and hydraulic performance evaluation, offering a simplified yet accurate alternative to more complex simulation-based approaches.

## 4. Conclusions

This research has made significant contributions to the understanding and optimization of fertigation systems, particularly through the detailed analysis of travel time dynamics within driplines. The final predictive equation enables irrigation designers to rapidly evaluate design trade-offs—such as emitter spacing, flow rate, or line length—without the need for full hydraulic simulations. This allows quicker decision-making during preliminary design and more efficient refinement of fertigation schedules.

The integration of advanced methodologies such as Python simulations and optimization techniques has led to several critical insights and practical advancements [40].

1) Impact of Flow Rate, Diameter, and Spacing: The study's comprehensive analysis of factors such as flow rate, diameter, and spacing has provided a deeper understanding of how these variables influence travel time. By developing predictive equations that account for these factors, the research offers valuable tools for designing more efficient irrigation systems. This optimization can be achieved by integrating the predictive model with agronomic parameters such as crop evapotranspiration (ET<sub>c</sub>), irrigation frequency, and soil infiltration rate. Based on these variables, the irrigation demand can be translated into an optimal emitter flow rate and required application volume. The model then allows testing various combinations of dripline diameter and emitter spacing to ensure that water and nutrients are delivered uniformly across the entire length within the desired irrigation window. This process enables system design to be tailored to specific crop requirements and environmental conditions, leading to improved water and nutrient use efficiency [41].

2) Exponential Growth of Travel Time: The identification of the exponential growth of travel time between drippers underscores the importance of velocity in fertigation systems. The inverse relationship between travel time and velocity reveals that as the speed of water flow decreases, the time taken for water to travel between drippers increases exponentially [13]. This finding is pivotal for practitioners aiming to optimize fertigation schedules, as it highlights the need to maintain appropriate flow velocities to ensure uniform distribution of water and nutrients [6].

3) Water travels 95% of the dripline length in approximately half of the total travel time: A significantly faster water flow in the initial portion of the dripline, followed by a substantial deceleration in the remaining 5% of the length. Despite the shorter distance, this final segment consumes a comparable amount of time to the initial 95%. In open field applications, this observation suggests a potential strategy: irrigation scheduling based on approximately half of the total calculated travel time may be a reasonable initial estimate. Further investigation is warranted to refine this approach and account for specific system characteristics and environmental conditions.

4) Optimization Techniques: The use of SciPy optimization techniques has fur-

ther refined the predictive models, resulting in high-fidelity equations that estimate travel times with remarkable precision. These equations are particularly useful for both entire driplines and specific segments, such as the 95% segment, which is critical for ensuring that nearly all plants receive adequate water and nutrients. This level of precision is essential for maximizing crop yields and resource efficiency [35] [42].

5) The developed equation provides a practical way to estimate the water travel time in drip irrigation systems, which is a valuable tool to support the hydraulic design process. However, it's crucial to point out that an inappropriate design—for example, excessive pipe lengths, incompatible flow rates, or inadequate diameters—can seriously compromise system efficiency, reducing the application uniformity coefficient (CU) below acceptable thresholds. This leads to an uneven distribution of water and nutrients, ultimately affecting crop productivity and resource use efficiency.

6) While the proposed model demonstrates a high degree of fitness and consistency with fundamental hydraulic principles, it is important to note that its validation has been based exclusively on simulation-generated data. Therefore, the travel time estimates should be considered as valid approximations under ideal operating conditions. The model assumes ideal operating conditions and does not account for common field realities such as pressure variability along the dripline or partial emitter obstruction. Future validation studies should also consider temperature-driven changes in water viscosity and slope-induced pressure variations.

This research represents a significant advancement in the field of agricultural irrigation, particularly in the optimization of fertigation systems. The insights gained from the analysis of travel time dynamics, coupled with the application of machine learning and optimization techniques, provide a robust framework for improving water and nutrient management. The practical tools and models developed through this research have the potential to transform fertigation practices, leading to more efficient, sustainable, and productive agricultural systems.

### Data Availability Statement

[https://github.com/greko-guevara/Advance Time driplines](https://github.com/greko-guevara/Advance_Time_driplines)

<https://zenodo.org/records/17591797>

### Conflicts of Interest

The authors declare no conflict of interest regarding the publication of this paper.

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