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Calibration of VISSIM Social Force Model Parameters:

Case Studies on Signalised Pedestrian Crossings at Min Bhawan and Pulchowk

by

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The undersigned certify that they have read and recommended to Institute of Engineering for acceptance, a thesis entitled **"Calibration of VISSIM Social Force Model Parameters: Case Studies on Signalized Pedestrian Crossings at Min Bhawan and Pulchowk)"**, submitted by **Pragyan Shrestha** in partial fulfilment of the requirement for degree of **Master of Science in Transportation Engineering**.

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ABSTRACT

Walking is a vital mode of transportation in urban areas like Kathmandu, yet pedestrian movement studies, particularly in the context of simulation, remain under-explored in Nepal. This study bridges this gap by calibrating Social Force Model (SFM) parameters in VISSIM to accurately simulate pedestrian movement at two signalised pedestrian crossings in Kathmandu. Seven key parameters were calibrated (Tau, ASocIso, BSocIso, Lambda, ASocMean, BSocMean, VD) to align simulated crossing speeds with observed speeds. A genetic algorithm was used for dynamic calibration, integrating VISSIM with a Python script. The final calibrated and validated SFM parameters were found to be (Tau, ASocIso, BSocIso, Lambda, ASocMean, BSocMean, VD) = (0.25, 0, 0.11, 0.5, 0.4, 0.01, 4). The results demonstrated a significant improvement in accuracy, with the calibrated parameters reducing the Root Mean Square Percentage Error (RMSPE) from 14% (default parameters) to 5%.

Keywords: Calibration, Genetic Algorithm, Pedestrian Simulation, Social Force Model, VISSIM

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LIST OF ABBREVIATIONS

COM	Component Object Model
GA	Genetic Algorithm
KDE	Kernel Density Estimation
RMSPE	Root Mean Square Percentage Error
SFM	Social Force Model

CHAPTER 1: INTRODUCTION

1.1 Background

Pedestrian movement is a critical component of urban mobility, particularly in cities such as Kathmandu, where walking constitutes 40% of all travel modes, with an average travel length of 3.0 km for pedestrians as compared to just 5.6 km for cars [1]. Walking not only offers a sustainable mode of urban transport, reducing congestion and emissions, but also promotes significant public health benefits through physical activity. Despite these reasons, pedestrian infrastructure in Kathmandu remains underdeveloped, leading to safety risks and inefficiencies. Pedestrians, along with bicyclists and motorcyclists, are considered vulnerable road users, but it is a matter of critical reflection to see if the real vulnerability lies in transport planning [2].

Urban pedestrian facilities include pedestrian crossings, footpaths, overhead bridges, subways, and bus stops. Among these, pedestrian crossings are particularly important from both traffic and safety perspectives, as they serve as shared spaces for vehicles and pedestrians. In urban areas with high pedestrian flow, signalised pedestrian crossings are essential for efficient traffic management and safety. Crossing speed and flow are key considerations in determining the signal timing and dimensions of pedestrian crossings.

The study of pedestrian movement is more complex than that of vehicles. Unlike vehicles confined to fixed lanes, pedestrians can freely choose routes according to the dynamic environment; the movement is largely influenced by their socio-psychological characteristics. Simulation based studies have widely been used for complex problems, including transportation [3]. In Nepal, while vehicle movement simulation studies have been conducted [4, 5], pedestrian movement simulation studies remain largely under-explored. Vehicle-centric development and complexity of pedestrian movement could be two major reasons [6].

One effective approach for studying pedestrian movement is the Social Force Model (SFM) developed by Helbing and Molnar in 1998 [7]. The model calculates pedestrian movement by considering “social-forces”—a combination of attraction forces towards the destination and repulsive forces from other pedestrians and physical obstacles. This model is reported to be able to simulate natural self-organising phenomena like lane-formation and stripe-formation and the advances in computational capabilities now make it feasible to simulate these complex dynamics [8]. Calibration, a process of fine-tuning model parameters to match real-world observations—is essential for accurate simulations. Here, calibration as an optimization problem, leveraging algorithms to systematically adjust parameters.

VISSIM—a microscopic traffic simulation software, has gained traction for vehicular modelling in Nepal but remains under-utilised for pedestrian studies. Although VISSIM integrates the SFM for pedestrian simulation, its default parameters may not be well-suited to local contexts, necessitating careful calibration. Inspired by machine learning's iterative optimization, this study employs genetic algorithms to systematically adjust these parameters, ensuring simulated speeds align with field observations at signalised pedestrian crossings.

This study aims to calibrate the Social Force Model (SFM) parameters in VISSIM to develop a more accurate pedestrian simulation model. Pedestrian crossings facilities are chosen for analysis due to their significance and ease of modelling due to well defined movement area, few origin-destination pairs. The focus is specifically on signalised pedestrian crossings, where SFM parameters are adjusted to fine-tune the simulated crossing speed distribution, ensuring alignment with observed crossing speeds.

1.2 Problem Statement

Pedestrian movement, despite being a fundamental aspect of urban mobility, remains significantly under-studied compared to vehicular movement, in Nepal. This is largely due to vehicle-centric development and the inherent complexity of modelling pedestrian behaviour. While VISSIM, a microscopic traffic simulation software, can effectively model pedestrian movement using the Social Force Model (SFM), its application in Nepal remains limited. This study addresses this gap by calibrating the SFM parameters in VISSIM using genetic algorithms, focusing on signalised pedestrian crossings to align simulated pedestrian crossing speeds with observed real-world data.

1.3 Objectives

The main objective of this study is to establish a foundation for pedestrian simulation studies by calibrating the Social Force Model (SFM) in VISSIM for accurate simulation of local pedestrian movement in Kathmandu. The specific objectives to achieve this are:

1. To calibrate Social Force Model parameters in VISSIM using genetic algorithms, ensuring simulated speeds align with observed speeds and validate them.

2. To compare the performance and theoretical consistency of the calibrated parameters against default values.

1.4 Scope of Study

This study focuses on developing and calibrating a pedestrian simulation model for signalised pedestrian crossings in Kathmandu using VISSIM. The scope includes the following key aspects:

1. The study focused on developing a pedestrian simulation model for two selected signalised crossings in Kathmandu, using VISSIM as the simulation platform.

2. It utilized observed pedestrian crossing speed data, collected during peak hours, to calibrate the Social Force Model (SFM).

3. A genetic algorithm was applied to calibrate the parameters, employing crossing speed as the performance measure to align simulated pedestrian speeds with observed speeds.

4. The calibrated parameters were compared against default values to assess both performance and theoretical consistency.

5. Finally, the study validated the calibrated parameters using independent data, with crossing speed again serving as the performance metric.

1.5 Limitations of Study

Despite its contributions, the study has certain limitations that should be considered:

1. Limited to Signalised Pedestrian Crossings
   The calibration is conducted only for pedestrian movement at signalised pedestrian crossings and does not account for other pedestrian facilities such as footpaths, overhead bridges, underpasses, or shared spaces.

2. Homogeneous Pedestrian Characteristics
   The study treats all pedestrians as a single type, without considering variations in age, gender, mobility impairments, or walking in groups, which could influence crossing behaviour.

3. No Pedestrian-Vehicle Interaction
   The study does not incorporate interactions between pedestrians and vehicles, which

are crucial for understanding pedestrian behaviour at un-signalised crossings or shared spaces.

4. Single Performance Metric for Calibration
   The calibration and validation process relies solely on pedestrian crossing speed as the primary metric. Other performance measures, such as waiting time, acceleration patterns, and density could enhance the model's accuracy but were not included in this study.

5. Limited Number of Study Areas
   The study is based on data from only two signalised pedestrian crossings in Kathmandu, which may not fully represent pedestrian behaviour across different locations in Nepal.

6. Temporal Resolution Limited to Hourly Data
   The study analyses pedestrian volume based on hourly data, without examining sub-hourly variations, which could provide more detailed insights into temporal fluctuations in pedestrian flow.

While these limitations provide opportunities for future research, the study successfully demonstrates the feasibility of calibrating SFM parameters for pedestrian simulation in VISSIM, paving the way for more comprehensive pedestrian mobility studies in Nepal.

1.6 Organisation of Report

This report is structured as follows:

Chapter 1: Introduction
This chapter provides an overview of the study, including background information, the problem statement, objectives, scope, and limitations.

Chapter 2: Literature Review
A review of relevant literature related to the study is presented in this chapter.

Chapter 3: Methodology
This chapter elaborates the research framework and methodology adopted for the study.

Chapter 4: Results and Discussion

This chapter presents the collected data, descriptive statistics, and the calibration and validation of the model. It also discusses the performance of the calibrated parameters and their theoretical consistency when compared to the default values.

Chapter 5: Conclusions and Recommendations

The final chapter summarizes the study's findings and provides recommendations for future research.

CHAPTER 2: LITERATURE REVIEW

2.1 Pedestrian Movement

The movement behaviour of pedestrians can be categorized into three hierarchical levels [9]:

1. Strategic level (minutes to hours)
   A pedestrian plans their route by listing destinations.

2. Tactical level (seconds to minutes)
   The pedestrian selects a route between destinations, considering the network layout.

3. Operational level (milliseconds to seconds)
   The pedestrian executes movement, avoiding oncoming pedestrians, navigating through crowds, or proceeding toward their destination.

Beyond these decision-making processes, pedestrian behavior is influenced by contextual factors, which are individual factors (e.g., age, gender, culture, physical abilities, group dynamics) and environmental factors (e.g., road design, lighting, traffic flow). These factors interact dynamically, making their modelling complex [10].

2.2 Pedestrian Modelling

Pedestrian modelling aims to mathematically replicate human walking behavior in diverse scenarios, ranging from routine commutes to emergency evacuations. Pedestrian modelling frameworks are broadly categorized into macroscopic, mesoscopic, and microscopic paradigms, each offering unique advantages depending on the application context [9].

1. Macroscopic Models
   These treat pedestrian flows as continuous fluids, governed by aggregate metrics like density-speed relationships. While computationally efficient for large-scale simulations (e.g., city-wide evacuation planning), they lack granularity to capture individual interactions or heterogeneous behaviors [11]. Example applications include hydrodynamic models for crowd dynamics in stadiums [12].

2. Mesoscopic Models
   These bridge macro- and micro-levels by grouping pedestrians into homogeneous clusters based on shared attributes (e.g., trip purpose, speed profiles). Queueing

network models are a common mesoscopic approach, simulating bottlenecks in transit hubs by treating pedestrian groups as discrete entities [13].

3. Microscopic Models
   Microscopic models prioritize individual agent behaviors. Among these, the Social Force Model (SFM) is particularly suited for simulating pedestrian traffic due to its ability to replicate natural self-organizing phenomena (e.g., lane formation) [8] and its integration into VISSIM. Other methods include:

   - Agent-Based Models
     Simulate autonomous agents with rules for navigation, collision avoidance, and goal-oriented decision-making. These excel in modelling heterogeneous populations (e.g., tourists vs. locals) and adaptive route choices, as demonstrated in studies of Hajj pilgrim flows [14].

   - Cellular Automata
     Discretize space into grids, with pedestrians transitioning between cells based on probabilistic rules. The computational efficiency suits high-density scenarios like metro station evacuations [15], but struggles with continuous motion.

   - Game-Theoretic Models
     Frame pedestrian interactions as strategic games, where agents optimize paths while anticipating others' moves. This approach captures competitive behaviors at bottlenecks but requires extensive behavioural data [16].

   - Data-Driven Models
     Machine learning leverages trajectory datasets to predict pedestrian movements. Hybrid frameworks combining neural networks with SFM have improved evacuation simulations in train stations [17].

2.3 Social Force Model and VISSIM

Social Force Model (SFM) is a popular microscopic model for pedestrian simulation, initially developed by Helbing and Molnar in 1998 [7]. The core principle of this model is that pedestrian motion is governed by "social forces," which represent internal motivations rather than physical forces exerted by the person or their environment. The resultant social force is composed of three components: the self-driving force, interactions between pedestrians, and forces exerted by obstacles or boundaries. A key feature of the model is its ability to reproduce natural effects like lane formation (counterflow) and stripe formation (crossing) [8]. Additionally, it characterises pedestrian movement behaviour through force analysis, similar to Newtonian mechanics [18]. It has been applied in various studies, such as pedestrian flow at bottlenecks in Germany [19], pedestrian movement on a skybridge in Indonesia [20], pedestrian traffic in a train station in Sweden [21], comparison of perceived vs simulated pedestrian level of service for a coastal area in Greece [22]. These studies were modelled in VISSIM.

VISSIM is a microscopic traffic simulation software that can simulate vehicle as well as pedestrian movement, with a wide range of options and parameters for accurate simulation. The pedestrian simulation in VISSIM is based on the SFM and was developed with collaboration with the original author of the model. The trajectories of pedestrians are not predefined but are calculated by the model, which makes simulation more flexible, detailed, and realistic [22]. It controls the operational and parts of the tactical levels of movement, whereas the user defines the settings of the strategic level [8]. The movement calculation is based on parameters of the SFM model, which are described in section 3.5.

2.4 Calibration Methodologies in Pedestrian Simulation

Calibration is the process of fine-tuning parameters of a model for it to accurately simulate a real-world phenomenon. The default values for the SFM parameters in VISSIM have been calibrated to generalized populations and facilities [23]. The local and site-specific behaviour may demand a different set of parameters.

Historically, researchers have calibrated microscopic models using macroscopic traffic flow parameters, such as flow-density relationships, or by relying on visual confirmation of self-organisation—approaches that may not always yield accurate results [24]. The structure of the Social Force Model (SFM) presents particular challenges for calibration, as many of its parameters are abstract and lack direct real-world analogues, making them difficult to measure empirically. These challenges are not unique to SFM; cellular automata and other agent-based models also encounter similar difficulties due to abstract parametrisation [25].

Recent studies use pedestrian speed [26, 19, 27, 20, 28], flow rates [26, 20], and detailed trajectory data [24] as key performance measures for more effective calibration and validation.

Various calibration approaches have emerged in response to these challenges. Some studies employ default parameters without modification [29, 26], while others use trial-and-error methods [19, 20] or sensitivity analysis [21]. More advanced techniques include genetic algorithms for advanced calibration [27, 28, 24].

Systematic Optimization Methods leverage computational algorithms to automate parameter tuning. Genetic Algorithms (GA), inspired by natural selection, iteratively evolve parameter sets to minimize simulation errors. Unlike trial-and-error approaches, GA efficiently explores high-dimensional parameter spaces, making it ideal for complex systems like pedestrian dynamics [30]. Studies in Nepal have applied GA to vehicle simulations [4, 5], but its potential for pedestrian SFM calibration remains untapped.

The GA process begins with a population of candidate solutions, each represented as a chromosome composed of genes that encode problem-specific information. Over multiple generations, these solutions evolve through selection, crossover, and mutation to improve their fitness. A fitness function evaluates how well each solution meets the problem's criteria. The process starts with the initialization of a random population, followed by selection, where individuals with higher fitness have a better chance of passing their genes to the next generation. Selection methods include roulette wheel selection, where individuals are probabilistically chosen based on fitness, and tournament selection, where the best among a randomly chosen subset of candidates is selected. Next, crossover combines genetic material from two parents to create offspring, either by swapping genes at a single point, multiple points, or randomly through uniform crossover. This helps maintain diversity while preserving good traits. To further enhance variation, mutation introduces small random changes to some genes, preventing stagnation and helping explore new solutions. Finally, the next generation is formed through replacement, which may involve completely replacing the old population or keeping the best individuals (elitism) to ensure progress. The algorithm repeats this process until a termination condition is met, such as reaching a predefined number of generations or finding an optimal solution [30].

Studies have identified key SFM parameters through sensitivity analysis and calibration. Sensitivity analyses of the parameters have primarily focused on the walking speeds of pedestrians, revealing non-linear relationships. Some studies have found that certain parameters are more sensitive to walking speed in specific settings. For instance, in India, sensitivity analyses of Tau, BSocIso, and ASocMean found them to be most sensitive to walking speed on skybridges, footpaths, and walkways [28]. In Greece, Tau, ASocMean, and BSocIso were found to be the most influential on walking speed at a train station, while ASocIso and VD had marginal effects [21]. Similarly, in Bosnia, Tau, ASocMean, and BSocIso had a greater influence on walking speeds on a footbridge [31], and in Indonesia, Tau, Lambda, ASocIso, and ASocMean exhibited significant influence on walking speed for a skybridge [20].

Additionally, various studies have reported calibrated values for these parameters in different settings:

- Signalized Pedestrian Crossings
  (Tau, ASocIso, BSocIso, ASocMean, VD) = (0.118, 1.052, 0.103, 0.3, 6.377) [27] (Indonesia)

- Footpath
  (Tau, ASocIso, BSocIso, ASocMean, VD) = (1.3, 0.1, 0.6, 0.1, 7.4) [28] (India)
  (Tau, ASocMean, Lambda, BSocMean, VD) = (0.4, 0.2, 0.5, 3.0, 22) [22] (Greece)

- Skybridge
  (Tau, ASocIso, BSocIso, ASocMean, VD) = (1.3, 0.1, 0.5, 0.1, 7.6) [28] (India)
  (Tau, ASocIso, BSocIso, ASocMean, BSocMean, Lambda, VD) = (0.2, 1.3, 0.2, 0.3, 0.4, 2.8, 6) [20] (Indonesia)

- Footbridge
  (Tau, ASocIso, BSocIso, Lambda, VD) = (0.06, 1, 0.10, 9) [31] (Bosnia)

2.5 Pedestrian Studies in Nepal

In Nepal, pedestrian simulation research remains underdeveloped, with most studies focusing on non-simulation approaches like regression analysis for waiting times [32] and Level of Service [33]. Calibration studies have been conducted for vehicular simulations [4, 5], though they remain unexplored for pedestrian simulations. The limited simulation-based research, such as [26]'s work on shared carriageways, relies exclusively on default SFM parameters without local calibration.

These studies demonstrate the critical role of parameter calibration in pedestrian microsimulation modelling, with trial-and-error approaches, sensitivity analyses, optimized calibration, and empirical validation being key techniques to enhance accuracy in pedestrian flow representation. While SFM and VISSIM are established tools, their application in Nepal requires context-specific calibration. Manual methods (e.g., trial-and-error) lack reproducibility, and existing Nepalese studies rely on default parameters. Genetic algorithms offer a systematic, data-driven solution, yet remain unexplored for pedestrian SFM calibration in Kathmandu. This study addressed this gap by adapting GA—previously used for vehicular simulations in Nepal—to optimize SFM parameters for accurate pedestrian simulation.

2.6 Calibration and Validation Statistics

Calibration relies on appropriate quantitative metrics to compare actual and simulated performance measures. Common approaches include goodness-of-fit measures and hypothesis testing. Goodness-of-fit measures assess the overall performance of simulation models, with popular choices being Root Mean Square Error, Root Mean Square Percentage Error (RMSPE), and Mean Absolute Percentage Error. Percentage error measures indicate the magnitude of errors relative to the average measurement. Also, RMSPE penalizes larger errors more heavily than smaller ones [34].

CHAPTER 3: METHODOLOGY

3.1 Methodological Framework

Building on the need for locally calibrated SFM parameters identified in Chapter 1, this study employs a genetic algorithm (GA) to optimize VISSIM's walking behavior parameters. The methodological framework (figure 3.1) treats calibration as an optimization problem, where the GA iteratively adjusts the SFM parameters responsible for pedestrian movement calculation to minimize discrepancies between simulated and observed crossing speeds. This approach is inspired from an aspect of machine learning workflows, where algorithms penalize deviations from target outputs. Here, Root Mean Square Percentage Error (RMSPE) serves as the fitness metric, with crossing speed distribution as the measure of effectiveness.

Pedestrian simulation in VISSIM is based on the Social Force Model (SFM), where the parameters are referred to as "Walking Behaviors." The SFM in VISSIM calculates the resultant force acting on a pedestrian and determines net movement (speed and direction) using ten parameters, which are explained later in Section 3.5.

The design of pedestrian crossings, including signal timing and width, is governed by pedestrian crossing speed and flow [35]. While flow depends on demand, speed is influenced by various contextual factors related to both individuals (e.g., physical ability, age, gender, culture) and the environment (e.g., road design, density, lighting).

These factors motivate the need for facility-specific SFM calibration, as default VISSIM parameters (section 3.5) do not account for pedestrian crossings-specific behaviors. In a facility like a pedestrian crossings, where origin-destination pairs are limited to two ends, calibration of crossing volume would be satisfied trivially if the input demand is correctly specified. However, calibration of crossing speeds may need modifying the SFM parameters because pedestrians in crossings have a strong motivation to cross despite high density, suggesting that they suppress repulsive forces and exhibit a stronger attraction toward their destination—a dynamic not captured by VISSIM's predefined "Walking Behaviors" (Default, Elevator (In Cab), and Elevator (Alighting)).

In the real world, psychological factors cause pedestrians to modify their walking behaviour on pedestrian crossings compared to other walking areas, whereas in VISSIM simulation, these speeds are dictated by the SFM parameters. The GA thus fine-tunes these parameters to ensure that the simulated speed distribution closely aligns with real-world observations.

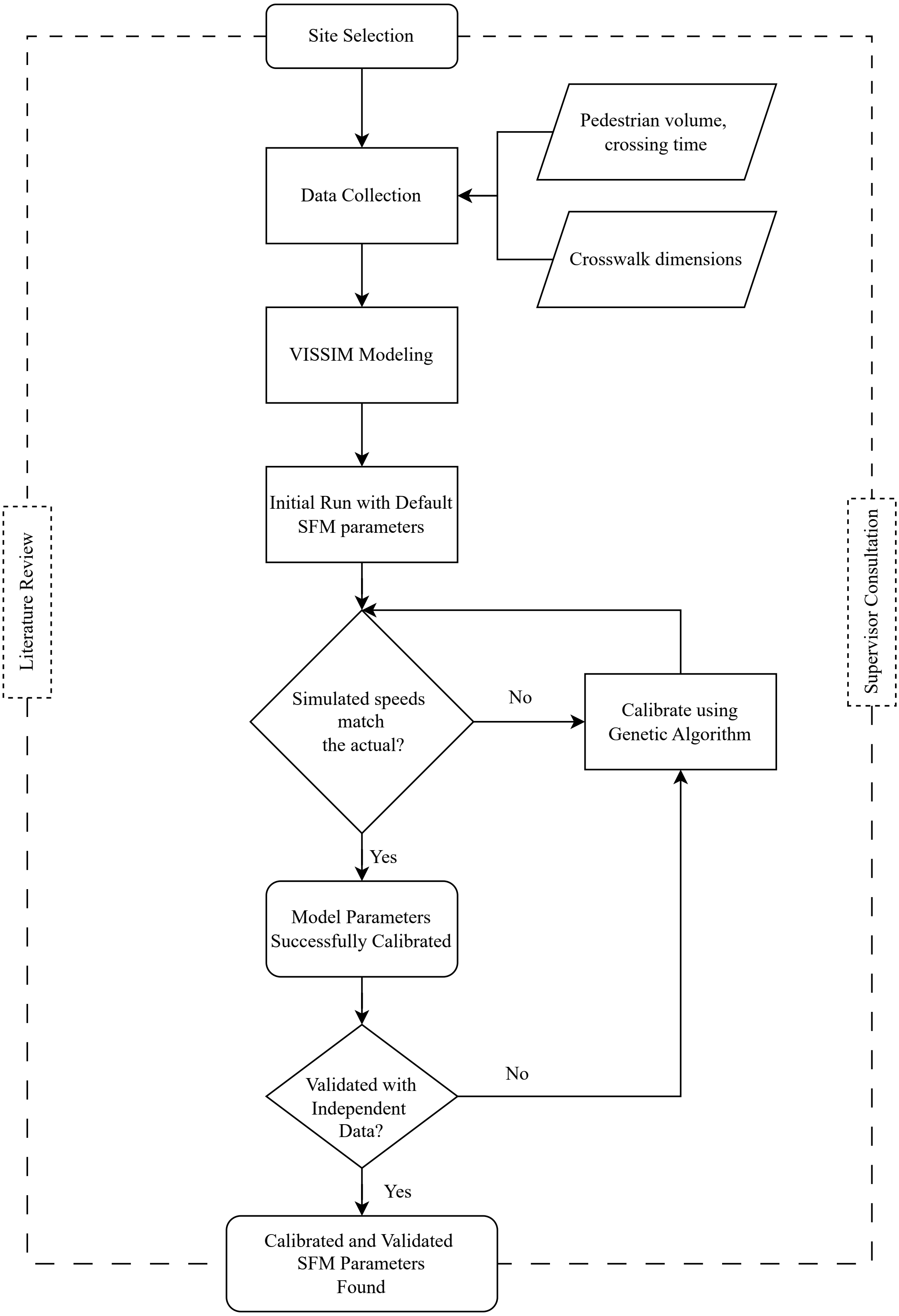


Figure 3.1: Research Framework

3.2 Study Area

Study areas were selected based on the following criteria:

1. Functional signalisation at the time of surveys

2. Considerable pedestrian flow

3. Well defined crossing region

4. Constraints of time and resources

Three study areas were initially selected, and video data were recorded for all of them. However, the pedestrian crossing at Damkal Chowk, Pulchowk was excluded from the analysis due to very low pedestrian volume, making meaningful calibration infeasible. The two remaining study areas, located in Kathmandu and Lalitpur districts, are shown in figure 3.2 and described below.

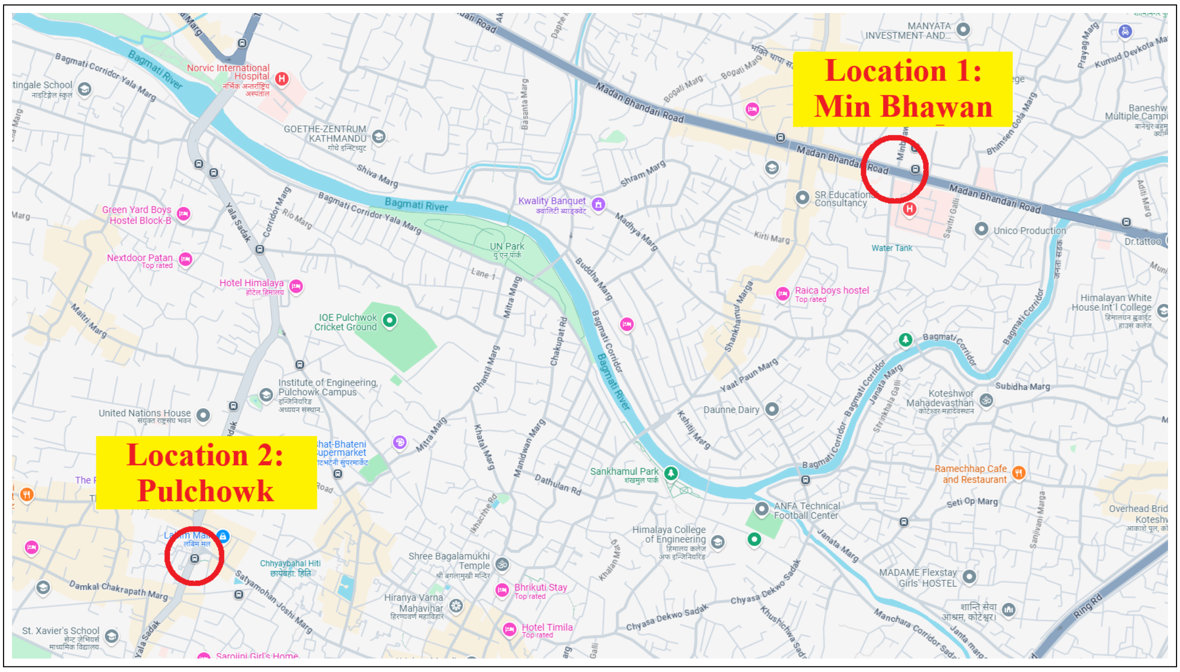


Figure 3.2: Map showing Study Locations

1. Min Bhawan

The pedestrian crossing is located at Min Bhawan, New Baneshwor, on Madan Bhandari Road, near Civil Service Hospital in Kathmandu. The road has four lanes, with a two-lane service road on each side. Figure 3.3 provides a photograph of the location. Only the pedestrian crossing on the main road is taken for analysis purposes, i.e., movement on service lanes are not considered.

Figure 3.3: Location 1: Min Bhawan

2. Pulchowk

The pedestrian crossing is located at Pulchowk, on Yala Sadak, on the south leg of the intersection near Labim Mall, Lalitpur. The road has four lanes. Figure 3.4 provides a photograph of the location.

Figure 3.4: Location 2: Pulchowk

3.3 Data Collection

Data collection was conducted through videographic surveys at each site for one hour each during morning and evening peak periods. A GoPro Hero11 camera was used to record footage at 1080p resolution (30 fps), ensuring clear visibility.

3.3.1 Travel Time Extraction

The travel time (crossing time) for each pedestrian was measured by recording timestamps at specific points. The start time was noted when the pedestrian's front foot entered the pedestrian crossing, while the end time was recorded when the front foot exited. For closely moving pedestrian groups, the crossing duration was recorded as a group since their times were identical, even if their start and end positions varied. Time measurements were captured with a precision of one second. To ensure accuracy, the MPV media player was used for timestamping, leveraging its frame-by-frame advancement feature with the "." and "," keys.

3.3.2 Speed Calculation

The individual crossing speeds were determined for all pedestrians by dividing their crossing distance by the corresponding crossing duration.

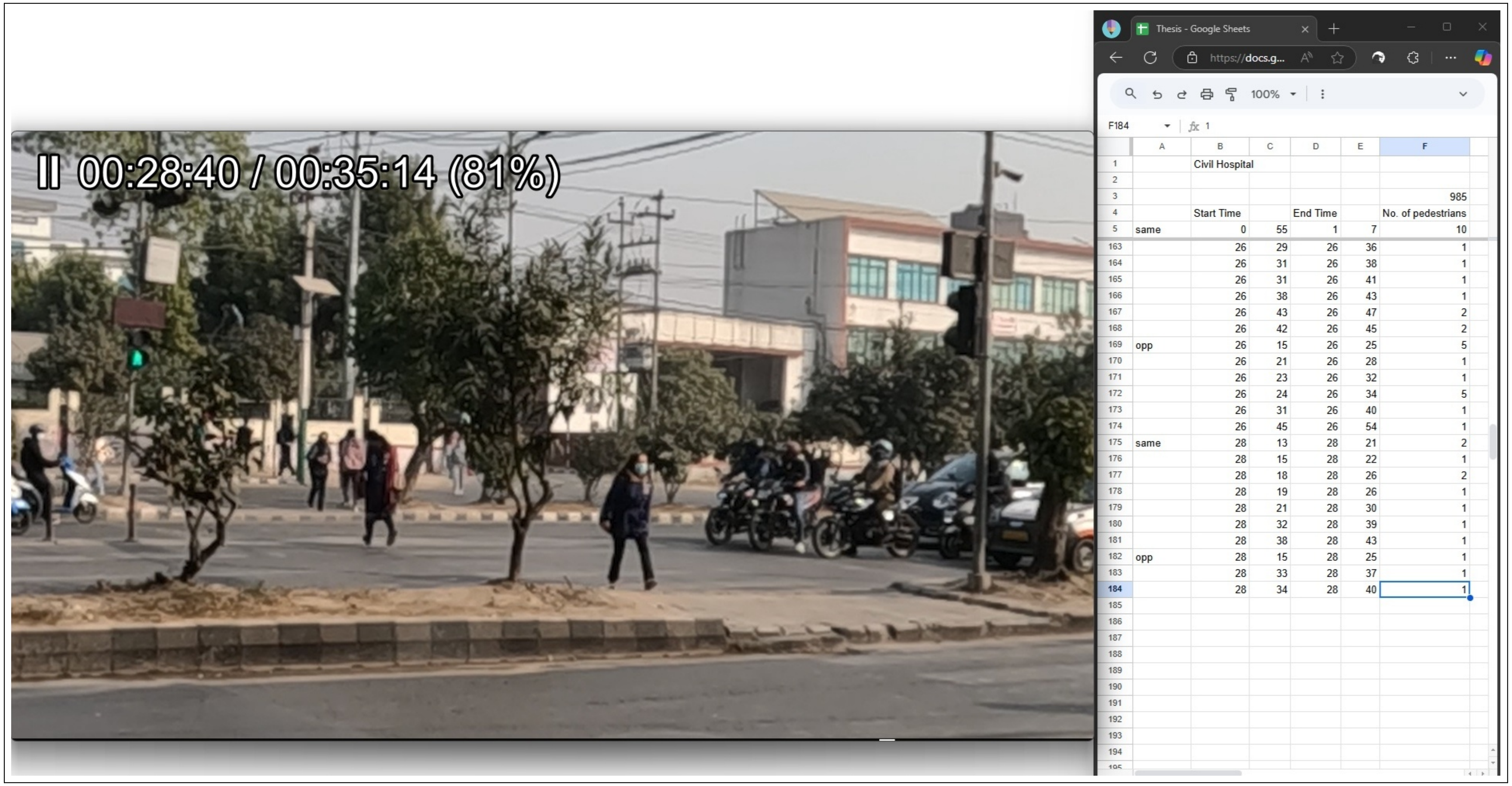
3.3.3 Quality Control

To ensure accuracy and consistency in data collection, several quality control measures were implemented. The video frames were clear enough visibility to ensure precise data extraction. Manual extraction was carried out meticulously, minimising errors. Pedestrians were only considered if they crossed during the walk signal phase to maintain consistency. Additionally, only uninterrupted movements were included, meaning any deceleration or avoidance manoeuvres were excluded from the analysis.

3.3.4 Site-Specific Observations

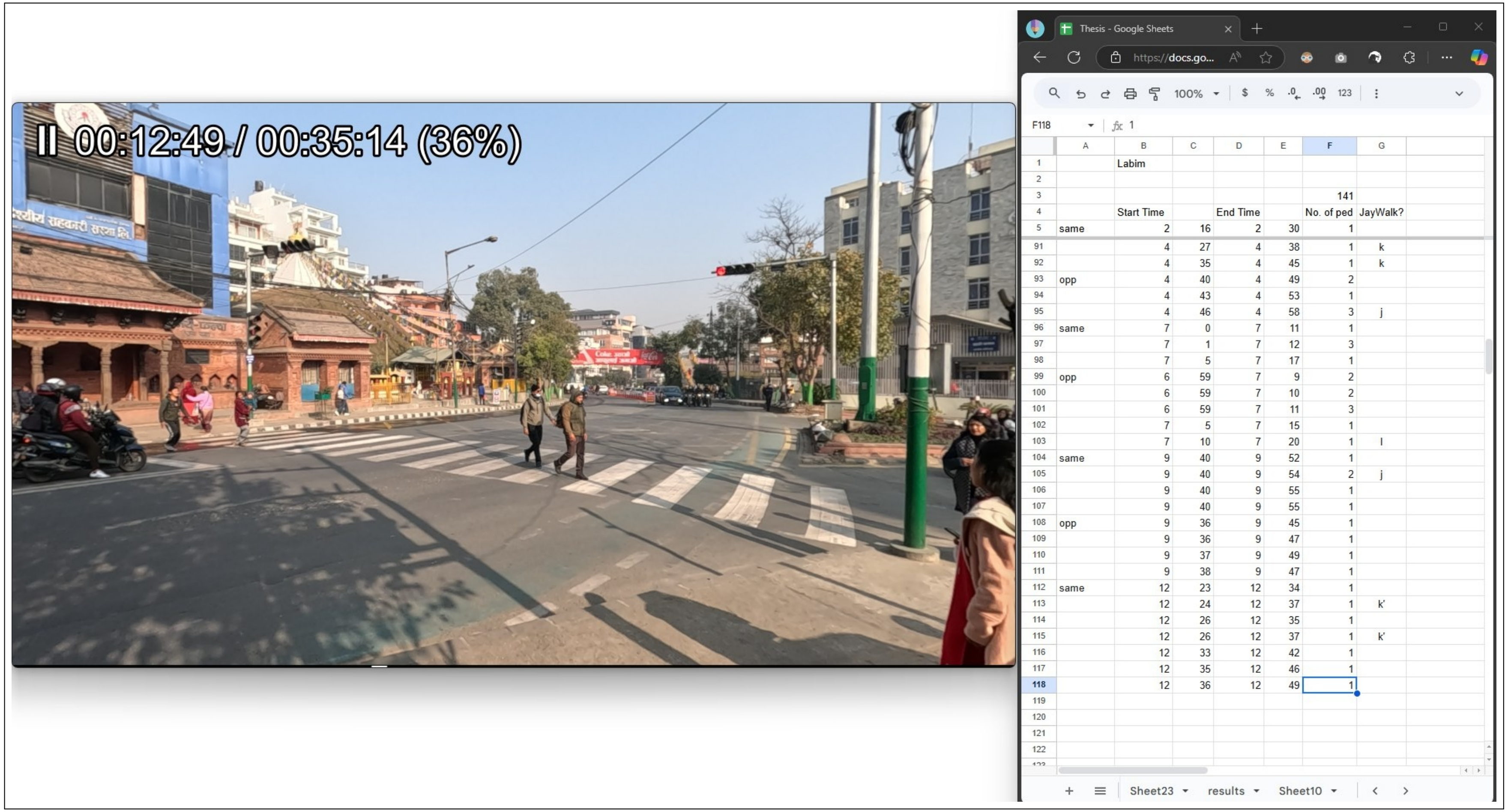
In location 1, pedestrian movement was confined to a well-defined area due to physical separators (service lanes). However, in location 2, pedestrians frequently entered/exited the pedestrian crossing offset from its ends. To address this, paths were labelled during extraction, and distances were adjusted accordingly.

Figures 3.5 and 3.6 illustrate the extraction processes for Locations 1 and 2, respectively.



	A	B	C	D	E	F
1		Civil Hospital				
2						
3						985
4		Start Time		End Time		No. of pedestrians
5	same	0	55	1	7	10
163		26	29	26	36	1
164		26	31	26	38	1
165		26	31	26	41	1
166		26	38	26	43	1
167		26	43	26	47	2
168		26	42	26	45	2
169	opp	26	15	26	25	5
170		26	21	26	28	1
171		26	23	26	32	1
172		26	24	26	34	5
173		26	31	26	40	1
174		26	45	26	54	1
175	same	28	13	28	21	2
176		28	15	28	22	1
177		28	18	28	26	2
178		28	19	28	26	1
179		28	21	28	30	1
180		28	32	28	39	1
181		28	38	28	43	1
182	opp	28	15	28	25	1
183		28	33	28	37	1
184		28	34	28	40	1

Figure 3.5: Video Data Extraction of Location 1



	A	B	C	D	E	F	G
1		Labim					
2							
3						141	
4		Start Time		End Time		No. of ped	JayWalk?
5	same	2	16	2	30	1	
91		4	27	4	38	1	k
92		4	35	4	45	1	k
93	opp	4	40	4	49	2	
94		4	43	4	53	1	
95		4	46	4	58	3	j
96	same	7	0	7	11	1	
97		7	1	7	12	3	
98		7	5	7	17	1	
99	opp	6	59	7	9	2	
100		6	59	7	10	2	
101		6	59	7	11	3	
102		7	5	7	15	1	
103		7	10	7	20	1	l
104	same	9	40	9	52	1	
105		9	40	9	54	2	j
106		9	40	9	55	1	
107		9	40	9	55	1	
108	opp	9	36	9	45	1	
109		9	36	9	47	1	
110		9	37	9	49	1	
111		9	38	9	47	1	
112	same	12	23	12	34	1	
113		12	24	12	37	1	k'
114		12	26	12	35	1	
115		12	26	12	37	1	k'
116		12	33	12	42	1	
117		12	35	12	46	1	
118		12	36	12	49	1	
119							
120							
121							
122							

Figure 3.6: Video Data Extraction of Location 2

3.4 VISSIM Modelling

VISSIM modelling includes creating the model, assigning field data such as volume, speed distribution, origin-destination pairs, including configurations for specific use cases. The following sections elaborate the modelling process in VISSIM for this study.

3.4.1 Model Creation

VISSIM model creation begins with defining the *Construction Elements*. Pedestrians can walk on *Area* elements as well as on *Link* elements marked as *Pedestrian Area*. Links designated as pedestrian areas are used for shared vehicle-pedestrian spaces like pedestrian crossing.

The pedestrian crossing was created based on field measurements. *Pedestrian Inputs* were provided for both directions as hourly volumes from collected data, with the *Exact* volume option selected. Signal Heads were placed at both ends of the pedestrian crossing and linked to *Fixed Signal Programs*. To ensure proper pedestrian initialization, the pedestrian input zone was positioned slightly away from the pedestrian crossing's starting edge. *Static Pedestrian Routing Decisions* were created for two opposing directions, each with a single route endpoint at the opposite side of the pedestrian crossing.

Figure 3.7 illustrates the VISSIM model network elements along with some of the configurations mentioned above.

3.4.2 VISSIM Configuration

The *Simulation Resolution* was set to the default value of 10 time steps per second, as recommended for pedestrian simulations [8]. The *Slow Down Distance* of *Signal Heads* was reduced from 3.0m to 0.5m since pedestrians were observed to wait very close to the pedestrian crossing edge.

For automatic calibration, feedback from VISSIM was required. To facilitate this, *Pedestrian Record* was enabled for *Direct Output* as a file after each simulation. This feature allowed export of detailed data for each pedestrian at every simulation second, including position, orientation, speed, dwell time, motion state, walking behavior, route, and more.

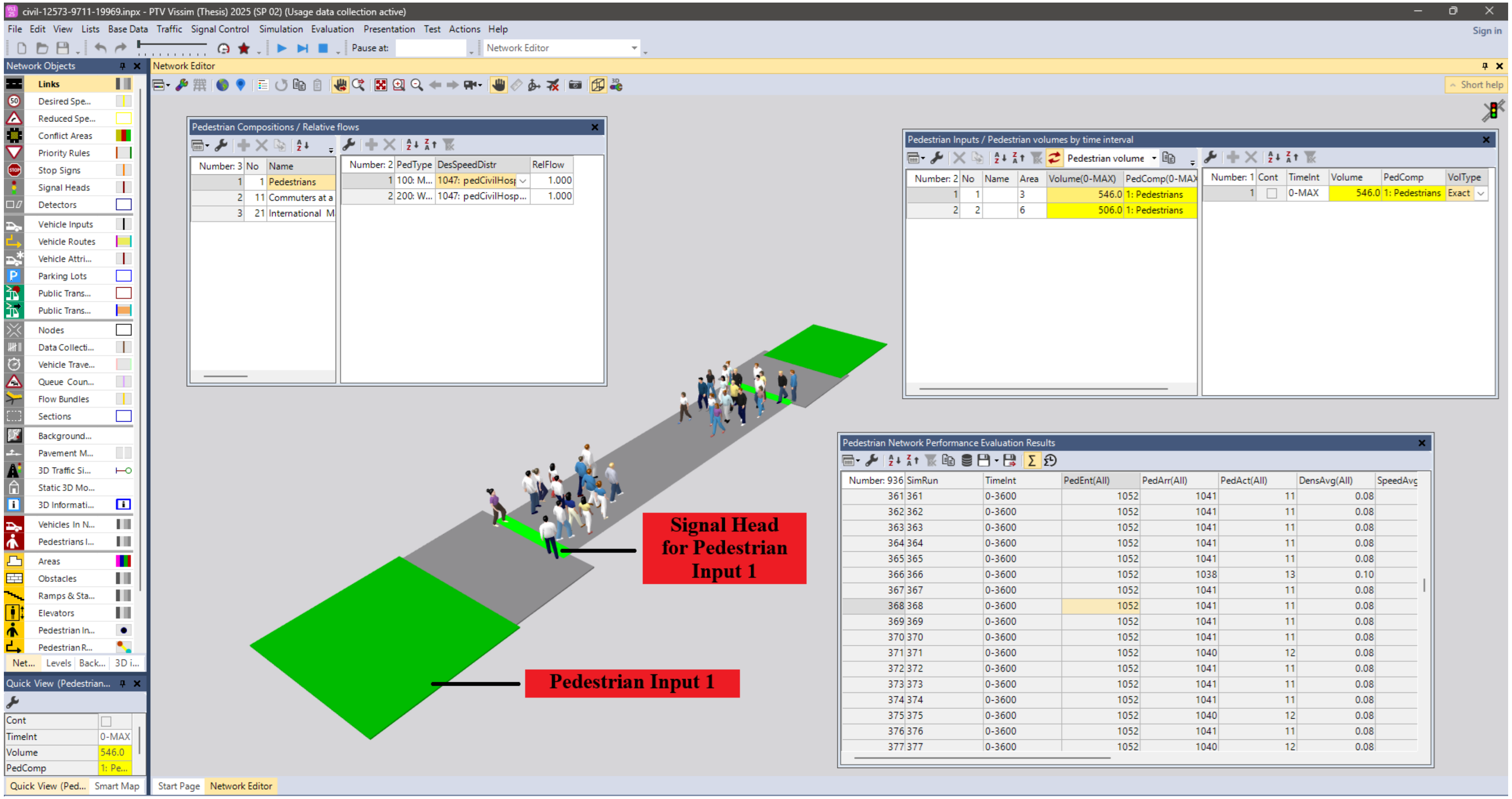


Figure 3.7: VISSIM Model Screenshot

In this study, for each pedestrian and each simulation second, the following data were exported:

- Speed
- Construction Element Type and Number
- Static Route Number

These outputs were used to compute the average crossing speed of each pedestrian on the pedestrian crossing.

Additionally, the *Pedestrian Network Performance Evaluation Results* provide aggregated metrics such as the number of pedestrians entered and arrived, as well as average speed, density, and travel time across the entire network. Among these, the number of pedestrians entered and arrived were exported. These values, along with the *Static Route Number* from the *Pedestrian Record* file, were used to validate the pedestrian flow data.

To improve simulation efficiency, the following configurations were applied through the calibration script:

- *QuickMode* was enabled.
- *UseMaxSimSpeed* was set to *TRUE*.
- The *GUI* was suspended.

3.5 SFM Parameters

The Social Force Model in VISSIM consists of 10 parameters that govern pedestrian movement in simulations. These parameters are described below according to the PTV VISSIM Manual 2025 [8], along with their theoretical impact on crossing speed.

1. **Tau**
   It represents the relaxation time or inertia that can be related to a response time, as it couples the difference between desired speed and desired direction. Increasing it decreases acceleration and density.
   The default value is 0.4, and has a lower limit of 0.05.
   So, higher values should decrease the crossing speed.

2. **ASocIso and BSocIso**
   A social (isotropic) and B social (isotropic), these parameters, together with another parameter, Lambda, influence the repulsive forces between pedestrians. Greater these values, greater is the repulsive force.
   The default values are 2.72 and 0.2, have lower limits 0 and 0.01 respectively.
   Since pedestrian crossings have limited space, so if pedestrians try to remain farther from each other, the crossing speed should be reduced if the flow is high enough.

3. **Lambda**
   It governs the amount of anisotropy of the forces from the fact that events and phenomena in the back of a pedestrian do not influence him (psychologically and socially) as much as if they were in his sight. Lesser values correspond to higher anisotropy.
   The default value is 0.176, and its value ranges from 0.1 to 1.0, where 1.0 means equal influence from front and back.
   So, higher values will result in having lesser frontal discriminatory influence, thus increasing the crossing speed.

4. **ASocMean and BSocMean**
   A social (mean) determines the strength of the repulsive force, while B social (mean) determines the range of the force. Greater these values, greater is the repulsive force.
   The default values are 0.4 and 2.8, have lower limits 0 and 0.01 respectively.
   Similar to isotropic, higher values should reduce the crossing speed.

5. **VD**
   Together with ASocMean and BSocMean, it determines how much the opposing pedestrians evade each other. Higher values result in greater evasion.
   The default value is 3, and has a lower limit of 0.
   Higher values make pedestrians avoid each other more, will increase the distance between pedestrians, and thus should increase the crossing speed if sufficient walking space is available.

6. **Noise**
   It is a random force added to the calculated force if a pedestrian remains below their desired speed for a certain time. The greater this value, the stronger is the random force added.
   The default value is 1.2, and has a lower limit of 0.
   Crossing speed should not be affected to changes to this parameter.

7. **ReactToN**
   During calculation of the total force for a pedestrian, only the influence exerted by the N closest pedestrians is taken into account.
   The default value is 0, and has a lower limit of 0.
   Higher values results in consideration of more number of pedestrians, thus maybe increase the resulting total repulsive force, thus reducing the crossing speed.

8. **SidePref**
   This parameter defines whether opposing pedestrian flows prefer using the right or the left side when passing each other.
   The default value is None, has other options as Right or Left.
   Crossing speed should not be affected to changes to this parameter.

Out of the 10 parameters, 7 were selected for analysis: Tau, ASocIso, BSocIso, Lambda, ASocMean, BSocMean, and VD. The remaining 3—Noise, ReactToN, and SidePref—were omitted, as all three were deemed insignificant according to the reviewed literature. Moreover, Noise and SidePref do not theoretically impact crossing speeds.

The parameter ranges were set based on literature review but were widened further to allow greater exploration, as the automatic calibration process could handle a broader range without concern for excessive number of values. However, visual inspection was conducted to prevent unrealistic pedestrian movement. Tau values below 0.2 caused pedestrians to disregard signals, while values above 2.0 led to unnaturally low density, so its range was set between 0.2 and 2.0. ASocIso had minimal impact, so a broad range up to 5.0 was chosen. For BSocIso, values above 0.5 resulted in excessive pedestrian spacing, reducing density unnaturally, leading to a range of 0 to 0.5. Lambda values over 0.6 caused some pedestrians to skip the signal head, so its range was set between 0 and 0.6. ASocMean values above 1.0 resulted in pedestrians walking unnaturally far apart, defining its range as 0 to 1.0. BSocMean showed minimal influence, so its range was extended up to 5.0, similar to VD, which also had negligible effects, leading to a range of 0 to 5.0.

3.6 Calibration

Crossing speeds of pedestrians were used as the key measure of effectiveness for the calibration process. The calibration was performed using a genetic algorithm implemented through the open-source module PyGAD [36]. VISSIM was controlled by a Python script utilizing the Component Object Model (COM) interface [37]. The script is provided in Appendix 5.2. A flowchart illustrating the calibration process and the genetic algorithm is shown in figure 3.8. Five calibrations were conducted for each site, using different seed values for the simulation. The genetic algorithm used for calibration is explained below, followed by a description of the calibration workflow.

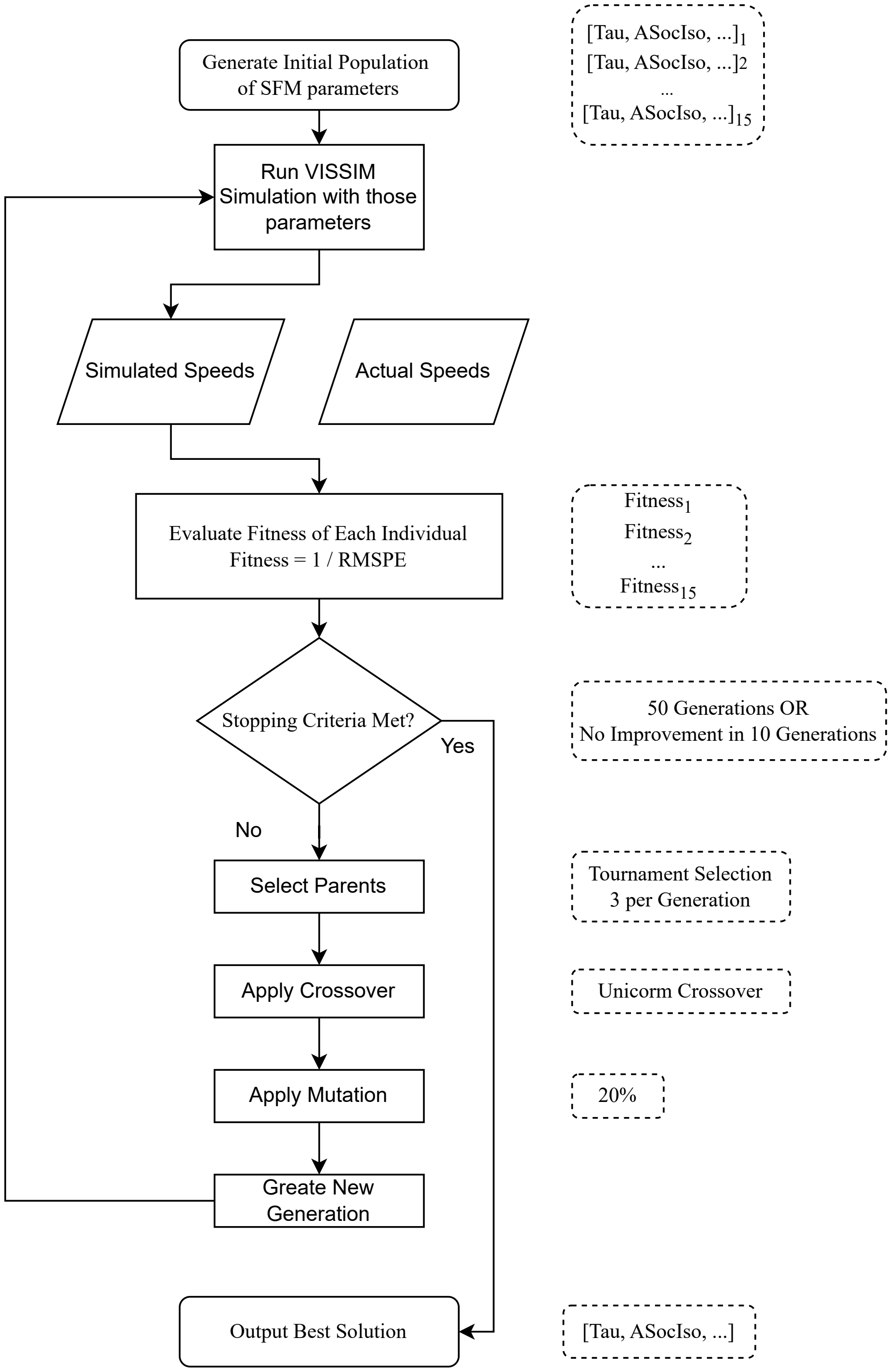


Figure 3.8: Calibration Flowchart

3.6.1 Genetic Algorithm

Genetic algorithm is an optimisation method inspired by natural selection. It evolves a population of candidate solutions over multiple generations by applying selection, crossover, and mutation. The process begins with an initial population, which is evaluated based on a fitness function. The best-performing individuals are selected as parents, and their genetic material is recombined through crossover to produce offspring. To maintain diversity and prevent premature convergence, mutations introduce small random changes. This iterative process continues until a stopping criterion is met, ensuring the algorithm finds an optimal or near-optimal solution. The GA parameters and their selected values are explained below, and the fitness function used was the reciprocal of the Root Mean Square Percentage Error (RMSPE).

1. **Population Size**
   The population size determines the number of candidate solutions in each generation. In this study, it was set to 15, which is twice the number of genes (the seven SFM parameters). A sufficiently large population ensures genetic diversity and reduces the risk of the algorithm becoming trapped in a local optimum. A small population may lead to premature convergence, while an excessively large one increases computational costs without necessarily improving performance.

2. **Number of Generations and Stopping Criterion**
   The number of generations was set to 50, allowing sufficient exploration of the solution space. However, to prevent unnecessary computation, a stopping criterion was implemented: if no improvement was observed over 10 consecutive generations, the algorithm terminated early. This approach ensured computational efficiency by avoiding excessive iterations when further improvements were unlikely.

3. **Random Seed for Reproducibility**
   Since the genetic algorithm (GA) relies on randomness, different executions can yield varying results. To ensure robustness, the algorithm was run five times with different random seed values for the VISSIM simulation. This approach allowed for the assessment of result consistency across multiple runs, minimizing the risk of drawing misleading conclusions from a single execution.

4. **Selection Method**
   The selection process determines which individuals contribute genetic material to the next generation. The *Tournament Selection* method was used, wherein a small subset

of individuals competes, and the best-performing one is selected. This method balances exploitation (favouring good solutions) and exploration (maintaining diversity). The algorithm selected three parents per iteration, ensuring a diverse genetic mix in the offspring.

5. **Crossover Method**
   The crossover mechanism combines genetic material from parents to generate new offspring. A *Uniform Crossover* approach was applied, wherein each gene in an offspring was randomly inherited from one of the parents rather than being copied from a fixed segment. This method increases genetic variation, improving the algorithm's ability to explore the solution space effectively.

6. **Mutation Strategy**
   Mutation introduces randomness to prevent premature convergence and maintain genetic diversity. A *Random Mutation* strategy was employed, where a randomly chosen gene in an offspring was modified. The mutation rate was set to 20%, meaning that 20% of the genes in the population underwent mutation in each generation. This moderate mutation rate preserved diversity without significantly disrupting well-performing solutions.

By carefully selecting these parameters, the GA was designed to efficiently search for high-quality solutions while maintaining diversity. The use of multiple random seeds further ensured the robustness of the results, minimising the influence of initial conditions. This approach allowed the GA to balance exploration and exploitation, leading to a more effective optimisation process.

3.6.2 Calibration Workflow

The calibration script followed the workflow outlined below:

1. A population of 15 sets of the seven SFM parameters was generated by the genetic algorithm (GA).

2. Each of those sets was applied to VISSIM one by one, and simulations were run.

3. After each simulation, pedestrian record data was configured to be exported as a file, capturing information for each pedestrian at each simulation second.

4. The pedestrian record data file was processed to compute the average speed of each pedestrian while on the pedestrian crossing, as well as the flow generated in the simulation.

5. The RMSPE between simulated and observed speeds was calculated as below.

$$RMSPE = \sqrt{\frac{1}{N}\Sigma_{i=1}^{N}\left(\frac{\text{Simulated Speed}_i}{\text{Observed Speed}_i} - 1\right)^2}$$

6. The GA applied selection, crossover, and mutation to generate the next generation of solutions with fitness as the reciprocal of RMSPE.

7. This process was repeated until either 50 generations had been explored or no improvement was observed over 10 successive generations.

8. The script also generated intermediate files for manual verification of the process.

CHAPTER 4: RESULTS AND DISCUSSION

4.1 Data Descriptives

Pedestrian crossings at both locations were situated on four-lane roads but differed in geometry and traffic flow. The data collected for each location is described below.

4.1.1 Location 1: Min Bhawan

For this location, the pedestrian crossing length considered includes only the main road, excluding service lanes. The pedestrian crossing was 14.30 m long and 4.0 m wide. Due to the presence of service lane separators, pedestrian movement remained well-defined within the pedestrian crossing width. The signal cycle length was 103 s with pedestrian walk phase of 30 s.

Pedestrian start and end times were recorded for alternate directions. The pedestrian flow was 546 from South to North and 506 from North to South in an hour. The average crossing speed was 1.57 m/s (5.64 km/h). The cumulative frequency distribution of speed is shown in table 4.1, which was used as the desired speed distribution in VISSIM. Speed values are reported in km/h, which is the preferred unit in VISSIM.

Table 4.1: Cumulative Frequency Distribution of speed for Location 1

speed (km/hr)	1.00	3.50	4.00	4.50	5.00	5.50	6.00	7.00	8.50	10.00	12.50	13.00
CDF	0.00	0.01	0.05	0.16	0.28	0.56	0.77	0.87	0.94	0.97	0.98	1.00

4.1.2 Location 2: Pulchowk

The designated pedestrian crossing length was 18 m for this location. However, the waiting area at the east end of the pedestrian crossing posed challenges for use due to psychological factors such as: the pedestrian crossing end being located at a bend, a vehicle lane from another adjacent leg of the intersection, and a longer crossing distance. As a result, many pedestrians chose to cross from about 5 m to the left of the marked pedestrian crossing. Since the left side of the road was usually clear of vehicles during pedestrian walk signals, their safety was not significantly compromised despite not starting at the designated position. A considerable number of pedestrians entered and exited at this location, often moving diagonally toward the midpoint of the pedestrian crossing. Field measurements were conducted to accurately determine the crossing distance, accounting for these deviations. This deviation increased the crossing distance by 1.30 m. Similarly, a few pedestrians exhibited the same behavior at the opposite end, entering and exiting from the sides. To ensure accuracy, video extraction included tracking pedestrian paths for precise crossing speed calculations. Table 4.2 summarises the observed flow patterns. The signal cycle length was 130 s with pedestrian walk phase of 30 s.

Pedestrian flow was recorded as 109 from east to west and 106 from west to east in one hour. The average crossing speed was 1.63 m/s (5.88 km/h). The cumulative frequency distribution of speed is presented in table 4.3, which was used as the desired speed distribution in VISSIM.

Table 4.2: Crossing patterns in Location 2

Crossing Pattern	Approach from		TOTAL
	East	West	
Straight Entry-Exit	84	75	159
Sideways Entry	11	4	15
Sideways Exit	13	26	39
Sideways Entry-Exit	1	1	2
TOTAL	109	106	215

Table 4.3: Cumulative Frequency Distribution of speed for Location 2

speed (km/hr)	3.00	3.50	4.00	4.50	5.00	5.50	6.00	6.50	7.00	7.50	8.00	8.50	9.00
CDF	0.00	0.01	0.02	0.05	0.19	0.42	0.65	0.85	0.89	0.96	0.97	0.99	1.00

4.2 Calibration

The VISSIM models for the two locations differed only in crossing's length and signal timing. Sideways entry and exit at location 2 were not simulated, as they resulted from site irregularities and were not relevant to the study's objective, which focused on calibration using crossing speed. However, to ensure accurate crossing speed calculations, the distances of sideways paths were carefully incorporated during data extraction. Calibration results of the two locations are discussed below.

4.2.1 Location 1: Min Bhawan

Firstly, simulation was run with default SFM parameters. Kernel Density Estimation (KDE) comparison of the simulated and actual speed distributions is presented in figure 4.1. The actual average pedestrian crossing speed was found to be 5.64 km/h, while the average simulated speed was 5.17 km/h. The RMSPE was 14.29%, and the distributions differed in both location and spread, indicating the need for calibration of the SFM parameters.

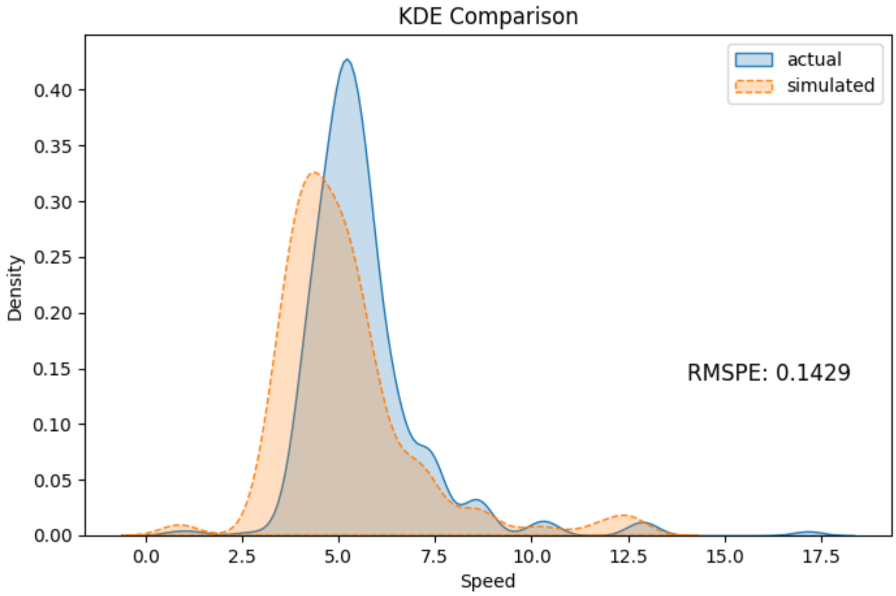


Figure 4.1: KDE comparison of Crossing Speeds: Actual vs. Simulated (Default SFM parameters) for Location 1

Table 4.4 presents five different calibration results for location 1, including the optimized SFM parameters and evaluation metrics. For instance, the first calibration process converged after 704 simulation runs and 25 generations of the Genetic Algorithm (GA). The calibrated parameters were found to be (Tau, ASocIso, BSocIos, Lambda, ASocMean, BSocMean, VD) = (0.5, 0, 0.06, 0.2, 0.6, 0.01, 3), resulting in an RMSPE of 6.57%. The entire calibration process took 31 hours on an Acer Nitro ANV15-51 with 16GB of RAM, a 13th Gen Intel(R) Core(TM) i7-13620H processor, and an NVIDIA GeForce RTX 4050 6GB graphics card.

KDE comparisons of simulated and actual crossing speeds for these five calibrated solutions are presented in figure 4.2.

The genetic algorithm effectively explored the range of values for the parameters during the calibration process, as shown in figure 4.3. This figure also highlights the best value found for each SFM parameter in each calibration, alongside the default value.

Table 4.4: Calibration Results for Location 1

Calibration L1	Default	Calib 1	Calib 2	Calib 3	Calib 4	Calib 5
GA						
Simulation		704	1327	636	931	398
Generation		25	50	23	34	14
SFM Parameters						
Tau	0.4	0.5	0.2	0.2	0.3	0.3
ASocIso	2.72	0	0	0.6	0.2	0
BSocIso	0.2	0.06	0.36	0.11	0.11	0.11
Lambda	0.176	0.2	0.5	0.1	0.5	0.25
ASocMean	0.4	0.6	0.55	0.45	0.85	0.15
BSocMean	2.8	0.01	0.01	0.01	0.01	0.01
VD	3	3	4	0	2	4
Evaluation						
RMSPE	14.29%	6.57%	5.19%	6.66%	7.51%	5.75%

The key findings from these calibrations are summarized below.

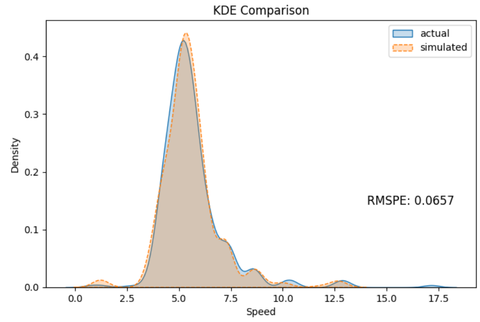
1. Tau was calibrated to a lower value than the default in four out of five calibrations, resulting in increased acceleration. In pedestrian crossings, pedestrians tend to walk faster due to a higher motivation to cross quickly, making this change theoretically consistent.

2. Higher values of ASocIso, BSocIso, ASocMean, and BSocMean increase the repulsive force between pedestrians, which reduces density. Except for ASocIso, all three were consistently lower than the default values, which would increase the speeds—this is also theoretically consistent.

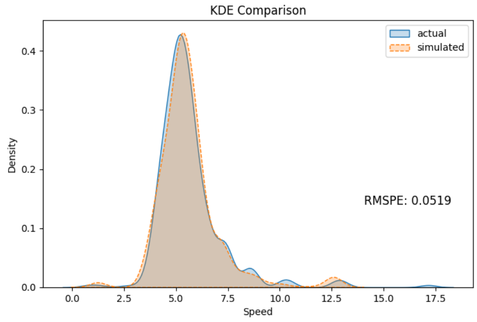
3. Lambda was higher than the default in most cases, reducing anisotropy. A lower anisotropy counteracts stronger frontal repulsion, improving counterflow efficiency—an expected behavior in pedestrian crossings, which is theoretically consistent.

4. The changes in VD were less consistent. This suggests that VD is less correlated with the crossing speed in this study.

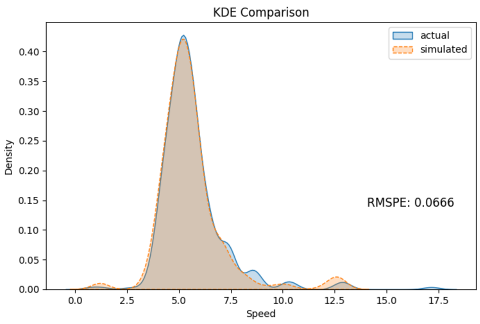
Due to variations in the calibrated solutions, other solutions were created using the most frequently occurring values (mode) from the five calibrated sets. Since ASocMean had no



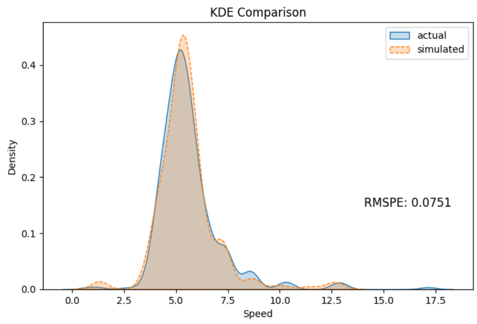
(a) Calibration 1



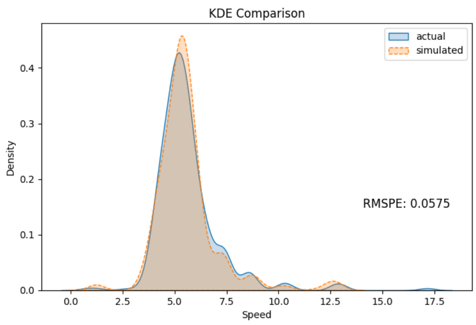
(b) Calibration 2



(c) Calibration 3



(d) Calibration 4



(e) Calibration 5

Figure 4.2: KDE Comparison of Crossing speeds: Actual vs. Simulated (Calibrations 1-5) for Location 1

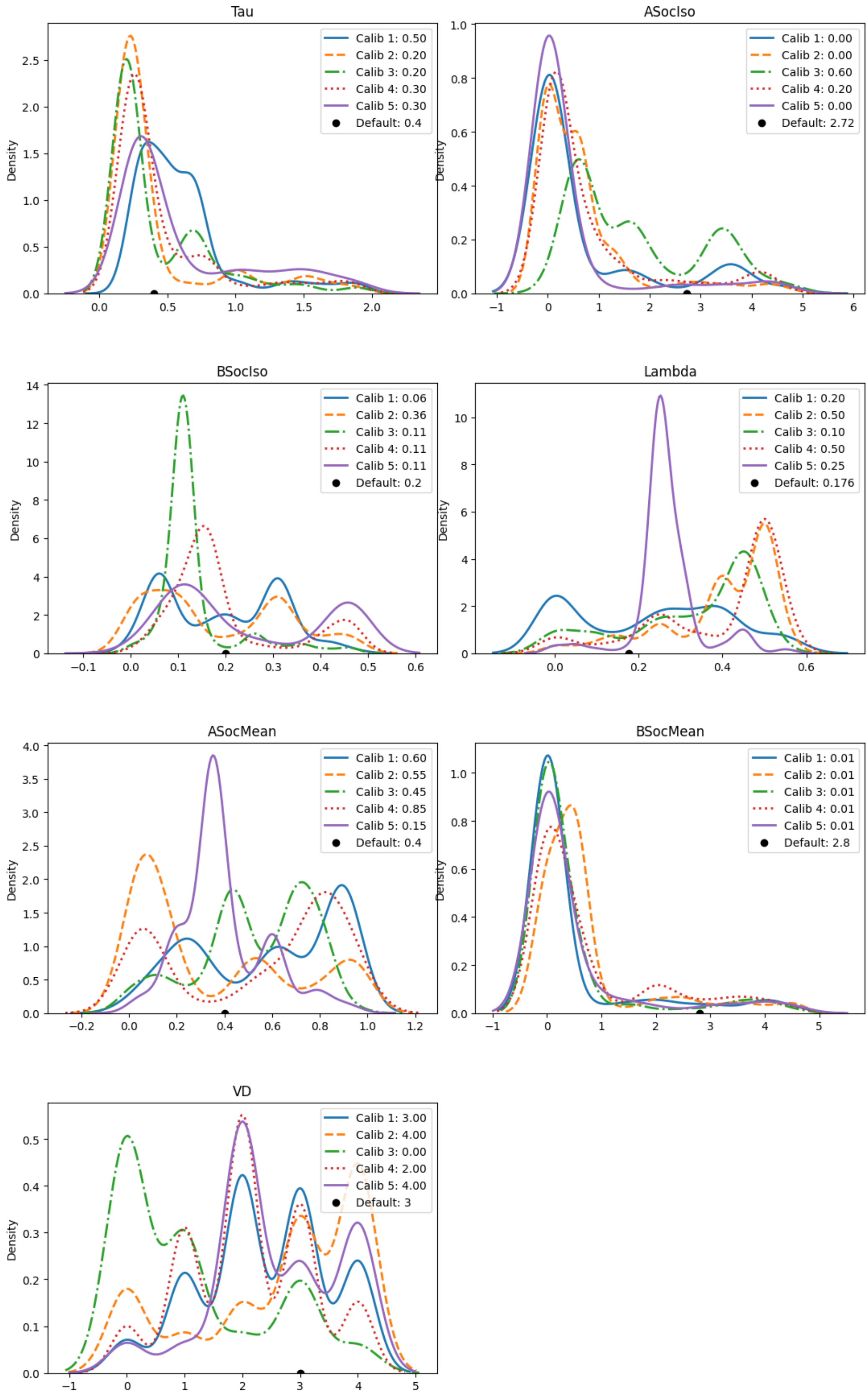


Figure 4.3: Parameters Values Explored by GA across 5 Calibrations for Location 1

repeating values, both its average and default values were considered. Table 4.5 presents these two options. The one with default value of ASocMean resulted in a lower error compared to the one with average value.

Table 4.5: Extra Solutions for Location 1

	Tau	ASocIso	BSocIso	Lambda	ASocMean	BSocMean	VD	RMSPE
Calib 6	0.25	0	0.11	0.5	**0.4**	0.01	4	4.72%
Calib 7	0.25	0	0.11	0.5	0.52	0.01	4	4.92%

Additionally, volume measurements from exported files confirmed that the generated directional volumes matched the input values exactly for all simulations in across calibrations.

4.2.2 Location 2: Pulchowk

Firstly, simulation was run with default SFM parameters. The comparison of the simulated and actual speed distributions is presented in figure 4.4. The actual average pedestrian crossing speed was found to be 5.88 km/h, while the average simulated speed was 5.17 km/h. The RMSPE was 14.29%, and the distributions differed in both location and spread, indicating the need for calibration of the SFM parameters.

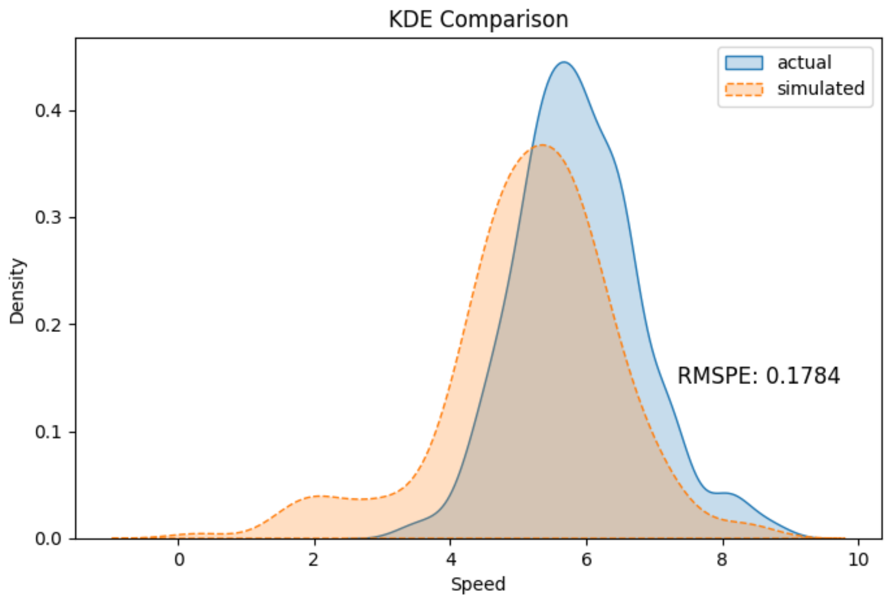


Figure 4.4: KDE Comparison of Crossing Speeds: Actual vs. Simulated (Default SFM parameters) for Location 2

Table 4.6 presents five different calibration results for location 2, including the optimized SFM parameters and evaluation metrics. The entire calibration process was completed in 7.5 hours.

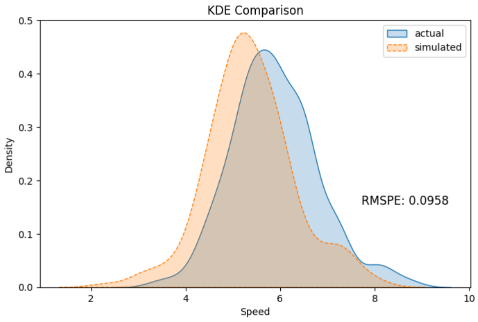
Comparisons of simulated and actual crossing speeds for these calibrated solutions are presented in figure 4.5. Additionally, the SFM parameter values explored by the GA during these five calibrations is illustrated in figure 4.6, along with the best value found for each SFM parameter in each calibration and the default value.

Table 4.6: Calibration Results for Location 2

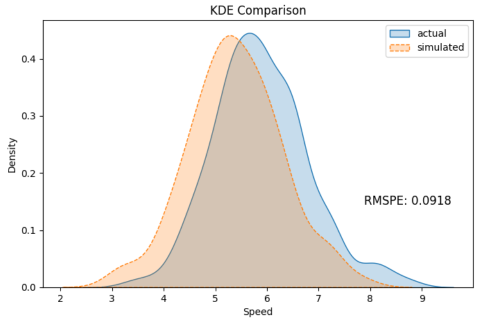
Calibration L2	Default	Calib 1	Calib 2	Calib 3	Calib 4	Calib 5
GA						
Simulation		805	623	540	998	1009
Generation		32	24	21	39	41
SFM Parameters						
Tau	0.4	0.9	0.8	0.8	0.9	0.9
ASocIso	2.72	0	0	0	0.2	0
BSocIso	0.2	0.01	0.21	0.16	0.11	0.16
Lambda	0.176	0.45	0.15	0.05	0.4	0.05
ASocMean	0.4	0.4	0	0	0.75	0.9
BSocMean	2.8	0.01	1.51	4.01	0.01	0.01
VD	3	2	2	1	3	1
Evaluation						
RMSPE	17.84%	9.58%	9.17%	9.45%	6.80%	7.72%

The comparison plots indicate that the simulated speeds for Location 2 do not match as closely with the actual speeds as they did for Location 1. This discrepancy may be attributed to the lower pedestrian flow at Location 2 (215 pedestrians) compared to Location 1 (1,052 pedestrians). With reduced pedestrian interactions, the feedback effect of the selected SFM parameters on crossing speed was diminished. As a result, the genetic algorithm may have struggled to identify an optimal direction for improvement across successive generations, leading to less effective calibration. Notably, the changes from default values followed similar directional trends (increase or decrease) for all parameters except Tau.

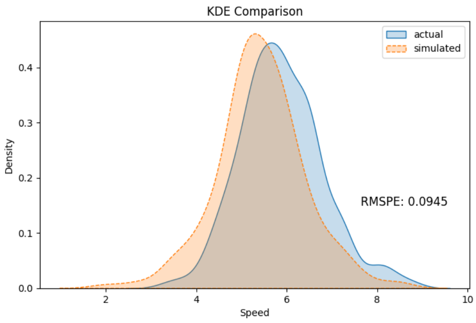
Similar to location 1, a new solution was created from the mode of values, resulting in an RMSPE of 7.43%, as shown in table 4.7, which is higher than for the third calibration's RMSPE of only 6.80%.



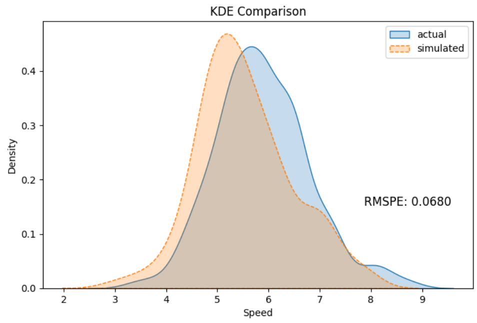
(a) Calibration 1



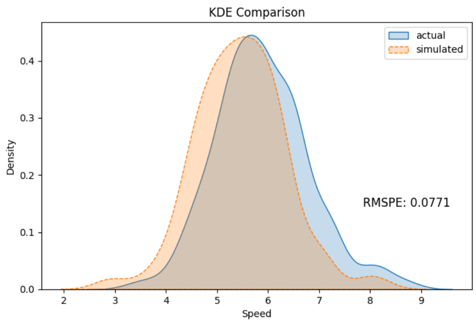
(b) Calibration 2



(c) Calibration 3



(d) Calibration 4



(e) Calibration 5

Figure 4.5: KDE Comparison of Crossing Speeds: Actual vs. Simulated (Calibrations 1-5) for Location 2

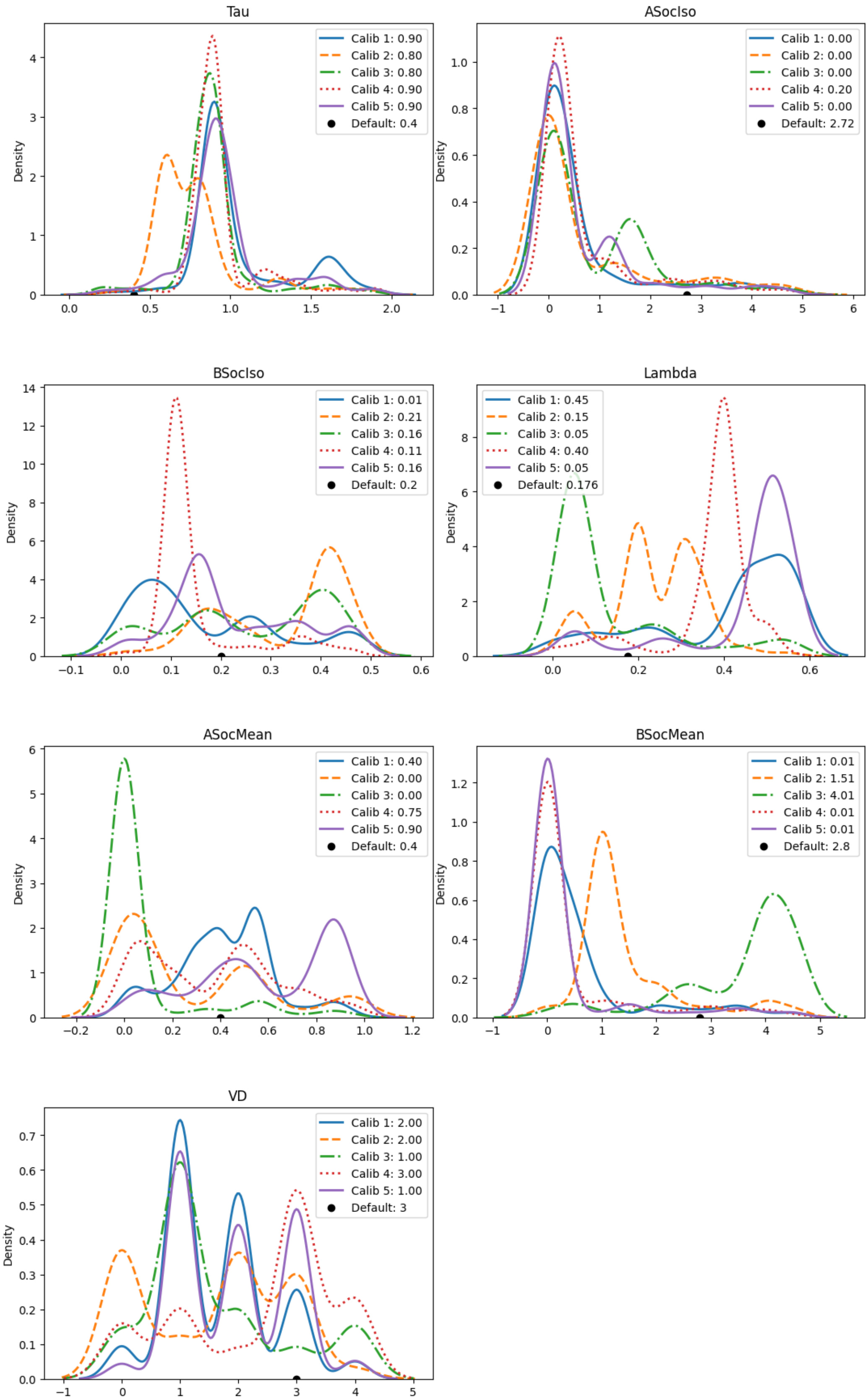


Figure 4.6: Parameters Values explored by GA across 5 Calibrations for Location 2

Table 4.7: Extra solution for Location 2

	Tau	ASocIso	BSocIso	Lambda	ASocMean	BSocMean	VD	RMSPE
Calib 6	0.9	0	0.16	0.05	0	0.01	2	7.43%

For this location as well, exported volume measurements confirmed that the generated directional volumes matched the input values across all simulations and calibrations.

4.3 Validation

Validation was conducted to assess the calibrated values and determine the best-performing parameters. The validation process was carried out using a separate dataset collected during the evening.

For Location 1, crossing speeds for 872 pedestrians were recorded over a 15-minute period, while for Location 2, 144 pedestrians were observed over a 35-minute period. The corresponding hourly volumes and observed speed distributions were set in VISSIM, and simulations were run using default and calibrated SFM parameters.

Tables 4.8 and 4.9 present the performance of the different calibrated solutions for Locations 1 and 2, respectively. The lower RMSPE values observed with the default parameters during validation compared to the calibration step may be attributed to the smaller sample size used for validation. Figures 4.7 and 4.8 illustrate this comparison between the simulated and actual crossing speeds for the validation dataset. Additionally, volume measurements matched the actual volumes.

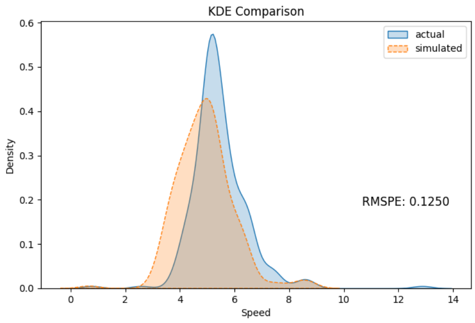
Hence, the calibrated solutions were successfully validated, as they yielded simulated crossing speeds closer to the observed speeds compared to the default parameters. Additionally, the changes in calibrated values from the default were consistent with theoretical expectations.

Table 4.8: Validation Results for Location 1

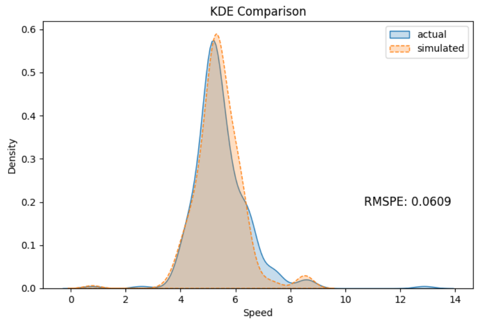
Validation L1	Default	Calib 1	Calib 2	Calib 3	Calib 4	Calib 5	**Calib 6**	Calib 7
Tau	0.4	0.5	0.2	0.2	0.3	0.3	0.25	0.25
ASocIso	2.72	0	0	0.6	0.2	0	0	0
BSocIso	0.2	0.06	0.36	0.11	0.11	0.11	0.11	0.11
Lambda	0.176	0.2	0.5	0.1	0.5	0.25	0.5	0.5
ASocMean	0.4	0.6	0.55	0.45	0.85	0.15	0.4	0.52
BSocMean	2.8	0.01	0.01	0.01	0.01	0.01	0.01	0.01
VD	3	3	4	0	2	4	4	4
RMSPE	12.50%	6.09%	6.21%	6.45%	6.22%	6.01%	**5.99%**	6.00%

Table 4.9: Validation Results for Location 2

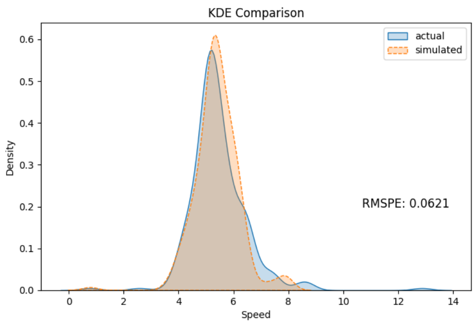
Validation L2	Default	Calib 1	Calib 2	Calib 3	Calib 4	Calib 5	Calib 6
Tau	0.4	0.9	0.8	0.8	0.9	0.9	0.9
ASocIso	2.72	0	0	0	0.2	0	0
BSocIso	0.2	0.01	0.21	0.16	0.11	0.16	0.16
Lambda	0.176	0.45	0.15	0.05	0.4	0.05	0.05
ASocMean	0.4	0.4	0	0	0.75	0.9	0
BSocMean	2.8	0.01	1.51	4.01	0.01	0.01	0.01
VD	3	2	2	1	3	1	2
RMSPE	13.81%	9.43%	8.96%	8.96%	10.26%	9.01%	9.46%



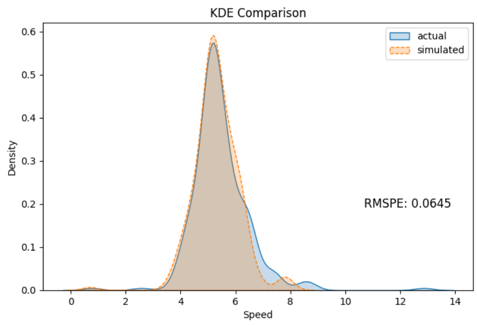
(a) Default



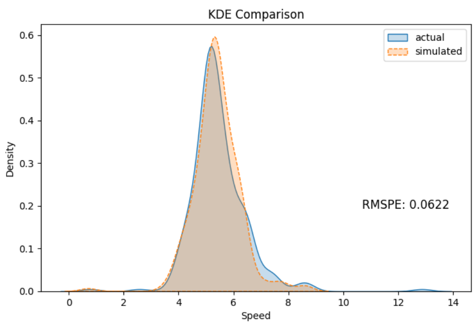
(b) Calibration 1



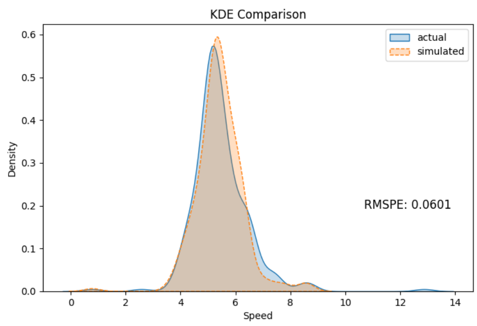
(c) Calibration 2



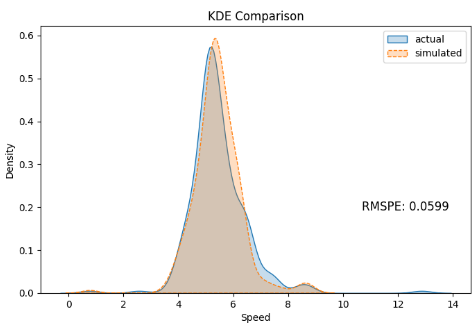
(d) Calibration 3



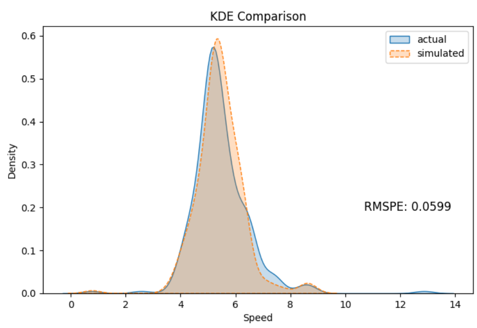
(e) Calibration 4



(f) Calibration 5

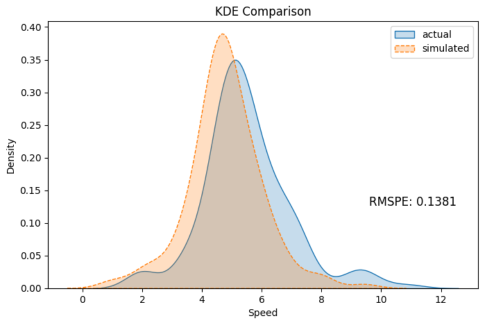


(g) Calibration 6

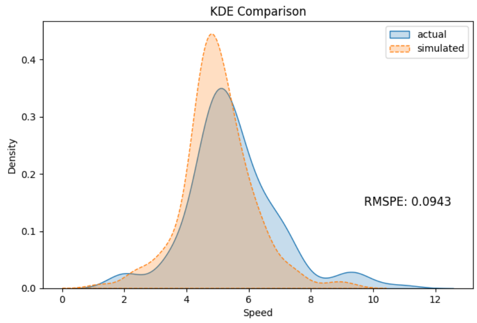


(h) Calibration 7

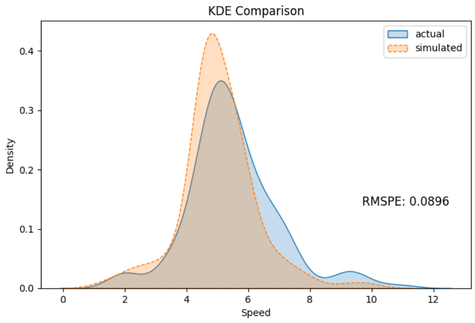
Figure 4.7: KDE Comparison of Crossing Speeds for Validation Data with Default and Calibrated SFM parameters for Location 1



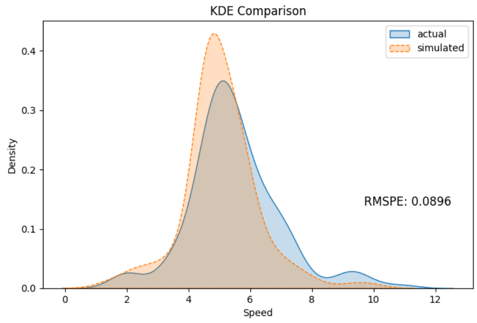
(a) Default



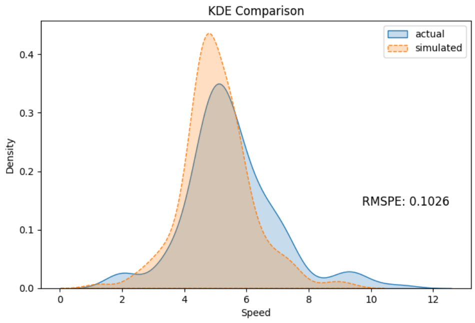
(b) Calibration 1



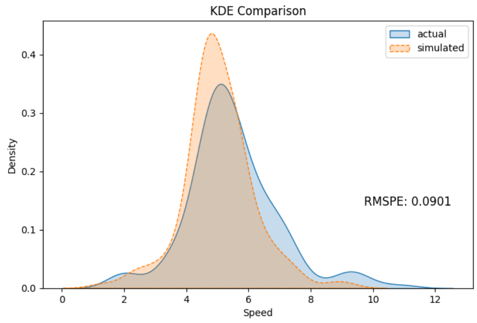
(c) Calibration 2



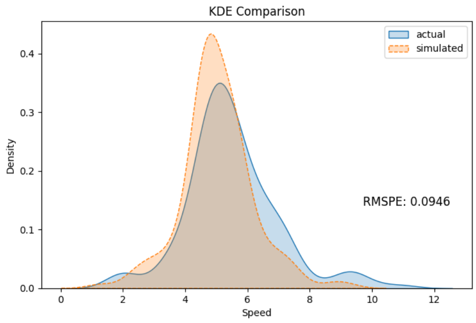
(d) Calibration 3



(e) Calibration 4



(f) Calibration 5



(g) Calibration 6

Figure 4.8: KDE Comparison of Crossing Speeds for Validation Data with Default and Calibrated SFM parameters for Location 2

4.4 Recommended Values

The calibrated solutions showed similar performance, despite variations in individual parameter values. However, consistent directional changes from the default values were observed. Notably, the recommended values for Locations 1 and 2 differed in the direction of change for Tau and Lambda, as summarized in table 4.10.

Table 4.10: Changes in Calibrated SFM Parameters for Locations 1 and 2

	Tau	ASocIso	BSocIso	Lambda	ASocMean	BSocMean	VD
Location 1	↑	↑	↑	↓	↓	↑	↑
Location 2	↓	↑	↑	↑	↓	↑	↑

Location 1 had a well-defined crossing zone, whereas Location 2 did not. However, crossing patterns were not rigorously incorporated into the calibration process; they were only considered for accurate crossing speed calculations. Since Location 1 was calibrated with significantly more data, Solution 6 from its calibration is recommended for pedestrian crossings in Kathmandu. The recommended SFM parameter values are listed again in table 4.11 along with their default values.

Table 4.11: Recommended SFM parameters

	Tau	ASocIso	BSocIso	Lambda	ASocMean	BSocMean	VD
Default	0.4	2.72	0.2	0.176	0.4	2.8	3
Recommended	0.25	0	0.11	0.5	0.4	0.01	4

4.5 Comparison with Other Studies

The calibrated recommended values from this study were compared with those found in the literature, as shown in table 4.12. For the same facility type—pedestrian crossing—analyzed in Philippines [27], the direction of change from the default values in both studies was the similar. The magnitudes of the calibrated values in this study were also close to those in the referenced study, except for Tau and VD, where the deviation was smaller in this study.

Blank cells in the table indicate that calibration was not performed for those parameters in the respective studies, meaning the default values were used instead.

Table 4.12: Comparison of Recommended Values with Other Studies

	Facility	Tau	ASocIso	BSocIso	Lambda	ASocMean	BSocMean	VD
Default		0.4	2.72	0.2	0.176	0.4	2.8	3
This Study	**Signalised Pedestrian Crossing**	**0.25**	**0**	**0.11**	**0.5**	**0.4**	**0.01**	**4**
[27] Philippines		0.118	1.052	0.103		0.3		6.377
[28] India	Footpath	1.3	0.1	0.6		0.1		7.4
[22] Greece		0.4			0.2	0.5	3	22
[28] India	Skybridge	1.3	0.1	0.5		0.1		7.6
[20] Indonesia		0.2	1.3	0.2	0.3	0.4	2.8	6
[31] Bosnia	Footbridge	0.06	1	0.1	0.1			9

CHAPTER 5: CONCLUSION

5.1 Conclusion

This study focused on calibrating the Social Force Model (SFM) parameters in VISSIM for signalised pedestrian crossings in Kathmandu, Nepal, to improve the accuracy of pedestrian movement simulations. Two key locations—Min Bhawan and Pulchowk—were selected as study areas, characterised by high pedestrian demand and good compliance, both situated on four-lane roads with an average pedestrian crossing speed of 1.6 m/s.

The calibration process employed a Genetic Algorithm (GA) to optimize seven SFM parameters (Tau, ASocIso, BSocIso, Lambda, ASocMean, BSocMean, VD), with pedestrian crossing speed as the primary performance measure. A Python script was developed to automate this process, utilizing the GA to dynamically adjust parameters by minimizing the Root Mean Square Percentage Error (RMSPE) between simulated and observed speed distributions. VISSIM's COM interface enabled automated parameter tuning and feedback, ensuring systematic exploration of the solution space. Validation was conducted using independent datasets to verify the robustness of the calibrated parameters.

The final calibrated parameters for Kathmandu's signalised crossings were determined as: (Tau, ASocIso, BSocIso, Lambda, ASocMean, BSocMean, VD) = (0.25, 0, 0.11, 0.5, 0.4, 0.01, 4).

These values significantly improved simulation accuracy, reducing the RMSPE from 14% (with default parameters) to 5%. Key changes included a lower Tau (indicating faster acceleration), reduced repulsive forces (ASocIso, BSocIso, BSocMean), and higher anisotropy (Lambda), which aligned with theoretical expectations for pedestrian behaviour in constrained environments—such as street crossings—where pedestrians are compelled to move forward despite limited space or interaction discomfort. Statistical validation confirmed the effectiveness of the calibrated model, showing consistent alignment between simulated and observed speed distributions across both study areas. This work establishes a foundation for context-specific pedestrian simulation in Nepal, addressing a critical gap in pedestrian modelling research.

5.2 Recommendation

Based on the findings of this study, the following recommendations are made for future research and practical applications:

- Use of Calibrated Parameters
  The calibrated SFM parameters should be adopted for simulating pedestrian movement at signalised crossings in Kathmandu, especially on four-lane roads with an average pedestrian speed of about 1.6 m/s. These calibrated parameters can also be applied in "what-if" scenarios to explore various pedestrian infrastructure designs, signal timings, and safety interventions, ultimately supporting urban planning and transportation strategies.

- Expansion to Other Facilities
  Future studies should extend the calibration process to different pedestrian environments, such as un-signalised crossings, footpaths, and public squares, to develop a more comprehensive pedestrian simulation model for Kathmandu.

- Incorporating Heterogeneous Pedestrian Behaviour
  Further research should classify pedestrians into different groups (e.g., slow walkers, groups, elderly, children) to better capture diverse walking behaviours rather than treating all pedestrians as a single type.

- Calibration Using Additional Metrics
  While this study focused on crossing speed, future studies should consider other aspects such as waiting time, acceleration patterns, density and pedestrian interactions like gap acceptance for a more complete model validation.

- Pedestrian-Vehicle Interaction
  To better understand multimodal interactions, pedestrian simulation should be integrated with vehicular traffic models to analyze pedestrian-vehicle conflicts and improve traffic signal optimization.

By addressing these areas, future research can build upon this study's findings to create more accurate, adaptable, and data-driven pedestrian simulation models for urban mobility planning in Nepal.

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APPENDIX A: CALIBRATION SCRIPT

This is the calibration script used in this study.

```
"""
VISSIM SFM Parameter Calibration using Genetic Algorithm
--------------------------------------------------------------

This script calibrates the Social Force Model (pedestrian
   walking behaviour) parameters in VISSIM using a genetic
   algorithm (GA) optimization approach.
The goal is to find parameter values that minimize the
   difference between simulated and observed pedestrian
   speeds.

Author: github/pragyanone
Based on: github/navs-svan/VISSIM-Pedestrian-Calibration
"""

import pygad
import shutil
import os
import win32com.client as com
import numpy as np
import pandas as pd


def set_vissim(resolution, seed, filename):
    """Initialize and configure a Vissim simulation
       instance.

    Args:
        resolution (int): Simulation resolution in
           simulation steps per second
        seed (int): Random seed for the simulation
        filename (str): Path to the Vissim network file (.
           inpx)

    Returns:
        com.Dispatch: Configured Vissim COM object
    """
    Vissim = com.Dispatch("Vissim.Vissim")
    Vissim.LoadNet(os.path.join(os.getcwd(), filename))

    End_of_simulation = 3600
    Vissim.Simulation.SetAttValue("SimPeriod",
       End_of_simulation)
```

```python
    Vissim.Simulation.SetAttValue("SimRes", resolution)
    Vissim.Simulation.SetAttValue("RandSeed", seed)

    Vissim.Evaluation.SetAttValue("PedNetPerfCollectData", 1)
    Vissim.Evaluation.SetAttValue("PedRecWriteFile", 1)

    Vissim.Graphics.CurrentNetworkWindow.SetAttValue("QuickMode", 1)
    Vissim.Simulation.SetAttValue("UseMaxSimSpeed", True)
    Vissim.SuspendUpdateGUI()

    for simRun in Vissim.Net.SimulationRuns:
        Vissim.Net.SimulationRuns.RemoveSimulationRun(simRun)
    return Vissim


def set_parameters(Vissim, parameter_list):
    """Set walking behavior parameters in Vissim simulation.

    Args:
        Vissim (com.Dispatch): Vissim COM object
        parameter_list (list): List of 7 parameter values in order:
            [Tau, ASocIso, BSocIso, Lambda, ASocMean, BSocMean, VD]
    """
    parameter_names = [
        "Tau",
        "ASocIso",
        "BSocIso",
        "Lambda",
        "ASocMean",
        "BSocMean",
        "VD",
    ]
    parameter_dict = {
        parameter_names[i]: parameter_list[i] for i in range(len(parameter_names))
    }
    Vissim.Simulation.Stop()
    for key, value in parameter_dict.items():
        Vissim.Net.WalkingBehaviors.ItemByKey(1).SetAttValue(key, value)


def get_data(SimCounter, filename):
```

```python
        """Process Vissim pedestrian output data and calculate speed statistics.

        Args:
            SimCounter (int): Simulation counter for file naming
            filename (str): Base filename for input/output files

        Returns:
            list: Sorted list of average pedestrian speeds
        """
        input_file = f"{filename}_{SimCounter:03}.pp"
        output_csv = f"gotdata_{filename}_{SimCounter:03}.csv"
        analysis_csv = f"pedestrian_speed_{filename}_{SimCounter:03}.csv"

        with open(input_file, "r") as file:
            lines = file.readlines()

        for i, line in enumerate(lines):
            if line.startswith("$PEDESTRIAN"):
                headers = line.strip().replace("$PEDESTRIAN:", "").split(";")
                data_lines = lines[i + 1 :]
                break
        else:
            raise ValueError("$PEDESTRIAN section not found in file")

        data = [line.strip().split(";") for line in data_lines if line.strip()]
        df = pd.DataFrame(data, columns=headers)

        df["NO"] = df["NO"].astype(int)
        df["SPEED"] = df["SPEED"].astype(float)
        df["CONSTRELNO"] = df["CONSTRELNO"].astype(int)

        df.to_csv(output_csv, index=False)

        df_filtered = df[
            (df["SPEED"] >= 0.2)
            & (df["CONSTRELTYPE"] == "Pedestrian link")
            & df["CONSTRELNO"].isin([1, 2])
        ]

        df_avg = df_filtered.groupby("NO")[["SPEED"]].mean().reset_index()
        df_avg.to_csv(analysis_csv, index=False)
```

```python
    df["PEDROUTSTA\\NO"] = df["PEDROUTSTA\\NO"].astype(int)
    flow_counts = df.groupby("PEDROUTSTA\\NO")["NO"].nunique()
    with open("flow_check.txt", "a") as f:
        f.write(
            f"{filename}_{SimCounter:03}, {flow_counts.get(1, 0)}, {flow_counts.get(2, 0)}\n"
        )

    return sorted(df_avg["SPEED"].tolist())


def len_equalizer(list1, list2):
    """Equalize lengths of two lists by trimming the longer one from both ends.

    Args:
        list1 (list): First input list
        list2 (list): Second input list

    Returns:
        tuple: Two lists of equal length
    """
    diff = len(list1) - len(list2)
    if diff == 0:
        return list1, list2
    longer, shorter = (list1, list2) if diff > 0 else (list2, list1)
    trim = abs(diff) // 2
    longer = longer[trim : trim + len(shorter)]
    return (longer, shorter) if diff > 0 else (shorter, longer)


def rmspe(actual, simulated):
    """Calculate Root Mean Square Percentage Error between two datasets.

    Args:
        actual (array-like): Observed/actual values
        simulated (array-like): Simulated values

    Returns:
        float: RMSPE value
    """
    actual, simulated = len_equalizer(np.sort(actual), np.sort(simulated))
```

```python
        return np.sqrt(np.mean(((actual - simulated) / (actual + 1e-10)) ** 2))


def read_frequency_table(filename):
    """Read CSV file containing speed frequency distribution data.

    Args:
        filename (str): Path to CSV file with 'speed' and 'no' columns

    Returns:
        numpy.ndarray: Expanded array of speed values
    """
    df = pd.read_csv(filename)
    data = np.repeat(df["speed"].values, df["no"].values)
    return data[data > 0]


def read_speed_data(filename):
    """Read CSV file containing individual pedestrian speed data.

    Args:
        filename (str): Path to CSV file with 'SPEED' column

    Returns:
        numpy.ndarray: Array of speed values
    """
    df = pd.read_csv(filename)
    return df["SPEED"].values


def fitness_func(ga_instance, solution, solution_idx):
    """Fitness function for genetic algorithm optimization.

    Args:
        ga_instance (pygad.GA): Genetic algorithm instance
        solution (list): Current parameter solution
        solution_idx (int): Index of current solution

    Returns:
        float: Fitness value (inverse of RMSPE)
    """
    global SimCounter, filename
    set_parameters(Vissim, solution)
    Vissim.Simulation.RunContinuous()
```

```python

    SimResult = get_data(SimCounter, filename)
    output = rmspe(actual_speeds, SimResult)

    log = f"Simulation: {SimCounter} \t {[f'{item:05.2f}' for item in solution]} \t rmspe: {output:.4f}"

    print(log)
    with open(f"output-{filename}.txt", "a") as file:
        file.write(log + "\n")

    fitness = round(1 / (output + 1e-8), 2)
    SimCounter += 1
    return fitness


def on_generation(ga_instance):
    """Callback function executed after each GA generation.

    Args:
        ga_instance (pygad.GA): Genetic algorithm instance
    """
    best_solution, best_solution_fitness, _ = ga_instance.best_solution()
    log = f"\nGeneration {ga_instance.generations_completed}: Best Solution = {[f"{item:05.2f}" for item in best_solution]}, Fitness = {best_solution_fitness:.2f}, RMSPE ={1/best_solution_fitness:.4f}"
    print(log)
    with open(f"output-{filename}.txt", "a") as file:
        file.write(log + "\n")


def genetic_algorithm():
    """Run genetic algorithm optimization for calibration of SFM parameters."""
    global SimCounter
    fitness_function = fitness_func
    num_generations = 50
    num_parents_mating = 3
    sol_per_pop = 15
    num_genes = 7
    parent_selection_type = "tournament"
    keep_elitism = 2
    crossover_type = "uniform"
    mutation_type = "random"
    mutation_percent_genes = 20
    gene_space = [
        {"low": 0.2, "high": 2, "step": 0.1},  # Tau
```

```
            {"low": 0, "high": 5, "step": 0.2},  # ASocIso
            {"low": 0.01, "high": 0.5, "step": 0.05},  # BSocIso
            {"low": 0, "high": 0.6, "step": 0.05},  # Lambda
            {"low": 0, "high": 1, "step": 0.05},  # AsocMean
            {"low": 0.01, "high": 5, "step": 0.5},  # BsocMean
            {"low": 0, "high": 5, "step": 1},  # VD
        ]

        # PARAMETER       DEFAULT VALUE
        # Tau             0.4
        # ASocIso         2.72
        # BSocIso         0.2
        # Lambda          0.176
        # ASocMean        0.4
        # BSocMean        2.8
        # VD              3

        ga_instance = pygad.GA(
            num_generations=num_generations,
            num_parents_mating=num_parents_mating,
            fitness_func=fitness_function,
            sol_per_pop=sol_per_pop,
            num_genes=num_genes,
            gene_space=gene_space,
            parent_selection_type=parent_selection_type,
            keep_elitism=keep_elitism,
            crossover_type=crossover_type,
            mutation_type=mutation_type,
            mutation_percent_genes=mutation_percent_genes,
            stop_criteria=["saturate_10"],
            on_generation=on_generation,
        )
        ga_instance.run()
        solution, solution_fitness, solution_idx = ga_instance.best_solution()
        log = (
            f"\n\nParameters of the best solution : {[f'{param:.2f}' for param in solution]}\n"
            f"Fitness value of the best solution = {solution_fitness:.2f}\n"
            f"rmspe value of the best solution = {1 / solution_fitness:.2f}"
        )
        print(log)
        with open(f"output-{filename}.txt", "a") as file:
            file.write(log + "\n")


```

```
SimCounter = 1
actual_speeds_file = "civil_actual.csv"
try:
    actual_speeds = read_frequency_table(actual_speeds_file)
except KeyError:
    actual_speeds = read_speed_data(actual_speeds_file)

filename = "civil"
Vissim = set_vissim(resolution=10, seed=10410, filename=filename + ".inpx")
genetic_algorithm()

for i in range(4):
    seed = np.random.randint(500, 20000)
    new_filename = f"{filename}-{seed}"
    shutil.copy(filename + ".inpx", new_filename + ".inpx")
    Vissim = set_vissim(resolution=10, seed=seed, filename=new_filename + ".inpx")
    SimCounter = 1
    filename = new_filename
    genetic_algorithm()
```

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[IOEGC16] Editor Decision

1 message

Bhesh Karki <conference-noreply@ioe.edu.np> Thu, Mar 27, 2025 at 8:12 AM
To: Pragyan Shrestha <079mstre014.pragyan@pcampus.edu.np>, Pradeep Kumar Shrestha <pradeep.shrestha@pcampus.edu.np>

Pragyan Shrestha, Pradeep Kumar Shrestha:

We are pleased to inform you that your manuscript titled "Calibration of Social Force Model Parameters in VISSIM: A Case Study of Signalised Crosswalk at Madan Bhandari Road, Civil Service Hospital, Kathmandu" submitted to 16th IOE Graduate Conference is **Accepted** for presentation in the Conference as well as inclusion in the Peer-Reviewed Proceedings. Please note that inclusion in hard copy proceedings is contingent upon your timely response to further edits, if any, during the publication process.

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With Warm Regards,
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Calibration of Social Force Model Parameters in VISSIM: A Case Study of Signalised Crosswalk at Madan Bhandari Road, Civil Service Hospital, Kathmandu

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Abstract
Walking is an essential mode of transportation in urban areas like Kathmandu, and pedestrian movement study is a crucial aspect of urban transport planning. However, it remains under-explored in Nepal, particularly in the context of pedestrian simulation. This study has addressed this gap by focusing on calibrating the Social Force Model (SFM) parameters in VISSIM for accurate simulation of pedestrian movement at a signalised crosswalk in Kathmandu. The model's parameters were calibrated to match the simulated crossing speed distribution with the observed crossing speed distribution. A genetic algorithm was employed for dynamic calibration by controlling VISSIM through a python script, to achieve optimised parameter values. The results showed improvement in representation of observed pedestrian behaviour, with the calibrated parameters providing significantly accurate simulation of pedestrian speeds than with the default parameters.

Keywords
Pedestrian Simulation, Social Force Model, VISSIM, Calibration, Genetic Algorithm

1. Introduction

1.1 Background

Pedestrian movement is a critical component of urban mobility, particularly in cities such as Kathmandu, where walking constitutes 40% of all travel modes, with an average travel length of 3.0 km for pedestrians as compared to just 5.6 km for cars [1]. Walking not only offers a sustainable mode of urban transport, reducing congestion and emissions, but also promotes significant public health benefits through physical activity. Despite these reasons, pedestrian infrastructure in Kathmandu remains underdeveloped, leading to safety risks and inefficiencies. Pedestrians, along with bicyclists and motorcyclists, are considered vulnerable road users, but it is a matter of critical reflection to see if the real vulnerability lies in transport planning [2].

The study of pedestrian movement is more complex than that of vehicles. Unlike vehicles confined to fixed lanes, pedestrians can freely choose routes according to the dynamic environment; the movement largely influenced by their socio-psychological characteristics. Simulation based studies have widely been used for complex problems, including transportation [3]. In Nepal, while vehicle movement simulation studies have been conducted [4, 5], pedestrian movement simulation studies remain largely under-explored. Vehicle-centric development and complexity of pedestrian movement may be two possible reasons.

One effective approach for studying pedestrian movement is the Social Force Model (SFM) developed by Helbing and Molnar in 1998 [6]. The model calculates pedestrian movement by considering "social-forces"—a combination of attraction forces towards the destination and repulsive forces from other pedestrians and physical obstacles. This model is reported to be able to simulate natural self-organising phenomena like lane-formation and stripe-formation and the advances in computational capabilities now make it feasible to simulate these complex dynamics [7].

VISSIM—a microscopic traffic simulation software—has gained traction for vehicular modeling in Nepal but remains under-utilised for pedestrian studies. Although VISSIM integrates the SFM for pedestrian simulation, its default parameters may not be well-suited to local contexts, necessitating careful calibration.

This study aims to calibrate the SFM parameters in VISSIM so as to develop an accurate pedestrian simulation model. It focuses on a case study of a signalised crosswalk, adjusting the SFM parameters to fine-tune simulated crossing speed distribution to align with the observed crossing speed distribution.

1.2 Problem Statement

Pedestrian movement, despite being a fundamental aspect of urban mobility, remains significantly under-studied compared to vehicular movement, in Nepal. This is largely due to vehicle-centric development [8] and the inherent complexity of modeling pedestrian behaviour [9]. While VISSIM, a microscopic traffic simulation software, can effectively model pedestrian movement using the Social Force Model (SFM), its application in Nepal remains limited. This study addresses this gap by calibrating the SFM parameters in VISSIM, focusing on a signalised crosswalk to align simulated pedestrian crossing speeds with observed real-world data.

2. Literature Review

2.1 Pedestrian Modeling and Related Studies

Pedestrians can be modelled at different levels of granularity: macroscopic, mesoscopic, and microscopic. At the macroscopic level, pedestrians are studied as a group, while at the microscopic level, the behaviour of individual pedestrians is modeled. The mesoscopic level lies between the two, where pedestrians are grouped into homogeneous sub-groups. Microscopic models provide great detail but are computationally intensive, with complexity increasing exponentially [10]. However, with the advancement in computing technology and traffic simulation software, the application of microscopic models have become feasible [11]. Various simulation models have been developed, such as simple network-based models, cellular automata models, physics-based models like the SFM, and data-driven approaches using machine learning and neural networks [10]. Among these, the SFM has been found widely used in areas like simulating vehicle-pedestrian interaction, evacuation, and safety management in large events [12].

Pedestrian related studies have been conducted in Nepal on some aspects. For instance, the waiting time of pedestrians at an unsignalised crosswalk in Kathmandu was modeled using Multinomial Logistic Regression, considering factors like infrastructure, vehicle flow, and pedestrian characteristics [13]. Similarly, regression analysis has been employed to model Pedestrian Level of Service at signalised intersections in Kathmandu [14]. Only one simulation-based study has been identified, which examines pedestrian flow on a shared carriageway at Mangal Bazaar, Patan using VISSIM using default parameters for SFM [15]. Calibration was assessed by comparing simulated volume with observed volume, however due to limited origin-destination pairs, the volumes would match trivially.

Calibration is the process of fine-tuning the parameters of a model for it to accurately simulate a real-world phenomenon. The default values for the SFM parameters in VISSIM have been calibrated to represent a moderately conservative average for an adult not in a mobility impaired group [16]. Moreover, the local and site-specific behaviour may demand a different set of parameters. Most researchers calibrate models using macroscopic traffic flow parameters, such as flow-density relationships, or visual confirmation of self-organisation. However, macroscopic calibration may not always be accurate [17]. Calibration has been found done using various techniques, including manual choice from arbitrary combinations [18, 19], trial-and-error methods [20], visual validation [21], and detailed trajectory data [22, 17]. For instance, [22] calibrated five parameters of the SFM (**Tau, ASocIso, BScoIso, AScoMean, VD**) to values (0.118, 1.052, 0.103, 0.300, 6.377) respectively in VISSIM, by comparing the actual speed profile of pedestrians with the simulated profile at crosswalk in Philippines. These results are discussed for comparison with that of the present study in section 3.3

Calibration, however, is beyond just fine-tuning parameters. For a simulation model to accurately reflect the real-world scenario, it needs to be specified from various aspects. Attention should be given for individual pedestrian characteristics differences based on gender, age, trip purpose, environment, facility, weather, etc [23, 24].

2.2 Social Force Model and VISSIM

Social Force Model (SFM) is a popular microscopic model for pedestrian simulation, initially developed by Helbing and Molnar in 1998 [6]. The core principle of this model is that pedestrian motion is governed by "social forces," which represent internal motivations rather than physical forces exerted by the person or their environment. The resultant social force is composed of three components: the self-driving force, interactions between pedestrians, and forces exerted by obstacles or boundaries. A key feature of the model is its ability to reproduce microscopic effects like lane formation (counterflow) and stripe formation (crossing) [7]. Additionally, it characterises pedestrian movement behaviour through force analysis, similar to Newtonian mechanics [25]. It has been applied in various studies, such as pedestrian flow at bottlenecks in Germany [18], pedestrian movement on a skybridge in Indonesia [20], pedestrian traffic in a train station in Sweden [23], comparison of perceived vs simulated pedestrian level of service for a coastal area in Greece [21]. These studies were modelled in VISSIM.

VISSIM is a microscopic traffic simulation software that can simulate vehicle as well as pedestrian movement, with a wide range of options and parameters for accurate simulation. The pedestrian simulation in VISSIM is based on the SFM and was developed with collaboration with the original author of the model. The trajectories of pedestrians are not predefined but are calculated by the model, which makes simulation more flexible, detailed, and realistic [7]. The movement calculation is based on the following parameters, as defined in the VISSIM Manual 2025.

1. **Tau**: It represents the relaxation time or inertia that can be related to a response time, as it couples the difference between desired speed and desired direction. Increasing it decreases acceleration and density.

   The lower limit is 0.05.

2. **ASocIso** & **BSocIso**: **A social (isotropic)** & **B social (isotropic)**, these parameters, together with another parameter, **Lambda**, influence the repulsive forces between pedestrians. Greater these values, greater is the repulsive force.

   The lower limits are 0 and 0.01 respectively.

3. **Lambda**: It governs the amount of anisotropy of the forces from the fact that events and phenomena in the back of a pedestrian do not influence him (psychologically and socially) as much as if they were in his sight. Lesser values correspond to higher anisotropy.

   Its value ranges from 0.1 to 1.0, where 1.0 means equal influence from front and back.

4. **ASocMean** & **BSocMean**: **A social (mean)** determines the strength of the repulsive force, while **B social (mean)** determines the range of the force. Greater these values, greater is the repulsive force.

   The lower limits are 0 and 0.01 respectively.

5. **VD**: Together with **ASocMean** & **BSocMean**, it determines how much the opposing pedestrians evade each other. Higher values result in greater evasion.

The lower limit is 0.

6. **Noise**: It is a random force added to the calculated force if a pedestrian remains below their desired speed for a certain time. The greater this value, the stronger is the random force added.

   The lower limit is 0.

3. Methodology and Findings

3.1 Data Collection and Descriptives

The signalised crosswalk on Madan Bhandari Road, near Civil Service Hospital in New Baneshwor, Kathmandu was selected due to its high pedestrian crossing volume. A videographic survey was conducted on Monday, January 28, 2025, from 9:30 AM to 10:30 AM. Pedestrian volume and crossing times were manually recorded from the video footage. A total of 904 pedestrians were observed crossing the intersection in both directions combined. Field measurements were taken to determine the dimensions of the crossing.

For each pedestrian, the crossing time was used to calculate their average crossing speed. The resulting data was right-skewed, indicating a few people cross faster than average, but very few cross extremely slowly. It followed lognormal distribution, with a mean of 1.60 m/s.

3.2 VISSIM Modeling

The model was created in VISSIM and pedestrian inputs were given as 450 pedestrians per hour from each direction. Simulation resolution was set to 10 time steps per second which is suitable [7]. First, the simulation was run on default SFM parameters and default speed distribution. Fig 1 shows the KDE comparison between actual and simulated speed distributions. Speed values are in kmph. Root Mean Square Percentage Error (RMSPE) was 38.47%, whereas p-value for Kolmogorov–Smirnov (KS) test is 0.00, indicating the distributions were not similar. Next, the observed speed distribution was assigned to the model, and the simulation was run. The comparison for this case is shown in fig 2. The RMSPE was reduced to 11.97% but the distributions still differed according to the KS test. This suggested that the SFM parameters needed calibration.

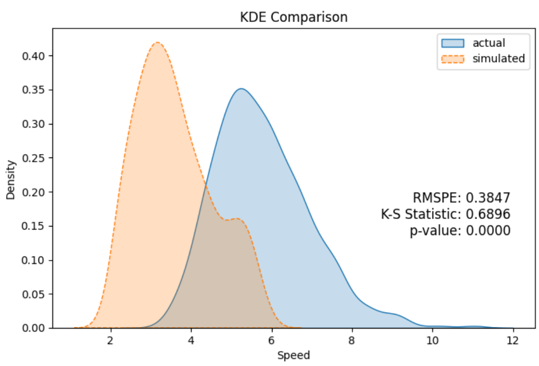

Figure 1: KDE comparison of actual vs simulated speeds with default SFM parameters and default speed distribution

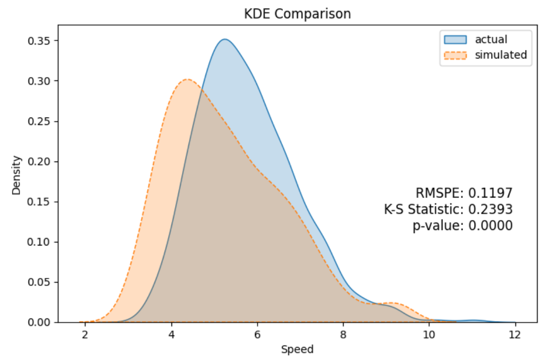

Figure 2: KDE comparison of actual vs simulated speeds with default SFM parameters but default speed distribution

3.3 Calibration

The SFM parameters in VISSIM were calibrated using a Python script, controlling VISSIM through the Component Object Model (COM) interface. Calibration was done with a genetic algorithm (GA) implemented using an open-source module, PyGad [26]. A simplified workflow of the calibration script is as follows.

```
SET SFM params in Vissim
RUN simulation and get
    simulated pedestrian speed data
CALCULATE p-value of KS test
    (actual vs simulated speed)
EVALUATE fitness based on p-value
SELECT new SFM params
    using genetic algorithm
IF stopping criteria met THEN BREAK
OUTPUT best SFM params
```

A genetic algorithm (GA) is a method used to find the best solutions by simulating natural selection. In this context, each parameter of the SFM is considered a gene. A set of these parameters forms a solution, which is represented as a chromosome. A collection of such chromosomes in one generation forms the population. The GA evolves the population over several generations by selecting the best solutions, combining them through crossover, introducing small changes through mutation, and applying selection to improve the results. This process ultimately leads to finding of the optimal set of parameters for the simulation.

Due to the inherent randomness of the genetic algorithm, it is important to have an adequate population size. In this case, the population size was set to 15, twice the number of genes (7). The number of generations to explore was set to 50, with a stopping criterion of no improvement over 10 generations. The calibration script was executed with four different random seed values.

Table 1 summarises the calibration results for four different seed values, including the calibrated SFM parameters and evaluation metrics. For instance, for the first seed value, the calibrated parameters were found to be (**Tau = 0.20, ASocIso = 0.00, BScoIso = 0.21, Lambda = 0.55, AScoMean = 0.00, BSocMean = 3.01, VD = 3**). The RMPSE was 1.9%, and the p-value for the KS test was 0.656. The calibration process saturated after 458 simulation runs in VISSIM, at the 18th generation of the genetic algorithm. Figures 3, 4, 5, and 6 illustrate the KDE comparisons for the four solutions.

Table 1: Simulation Results for Various Runs

Calibration	Default	Calib1	Calib2	Calib3	Calib4
Parameters					
Tau	0.40	0.20	0.40	0.20	0.40
ASocIso	2.72	0.00	0.00	0.20	0.20
BSocIso	0.20	0.21	0.36	0.11	0.26
Lambda	0.176	0.55	0.10	0.55	0.55
ASocMean	0.40	0.00	0.00	0.30	0.15
BSocMean	2.80	3.01	2.01	0.01	0.01
VD	3	3	2	0	3
Metrics					
RMSPE	0.120	0.019	0.033	**0.018**	0.022
p (KS test)	0.000	**0.656**	0.475	0.272	0.548
SimRun		458	300	1017	350
Generation		18	13	40	23

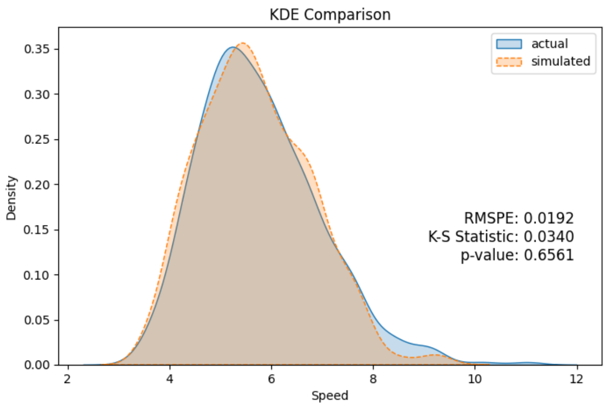

Figure 3: KDE comparison of actual vs simulated speeds with with solutions from calibration 1

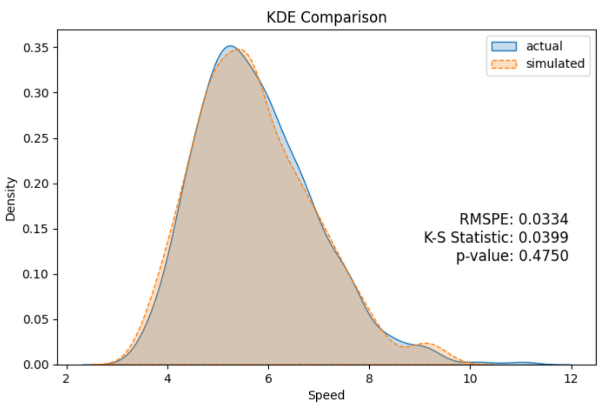

Figure 4: KDE comparison of actual vs simulated speeds with solutions from calibration 2

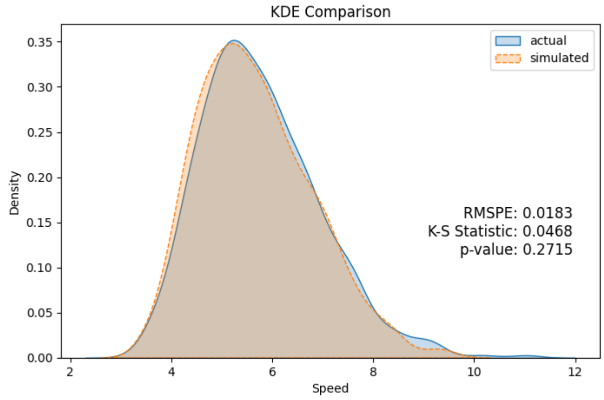

Figure 5: KDE comparison of actual vs simulated speeds with with solutions from calibration 3

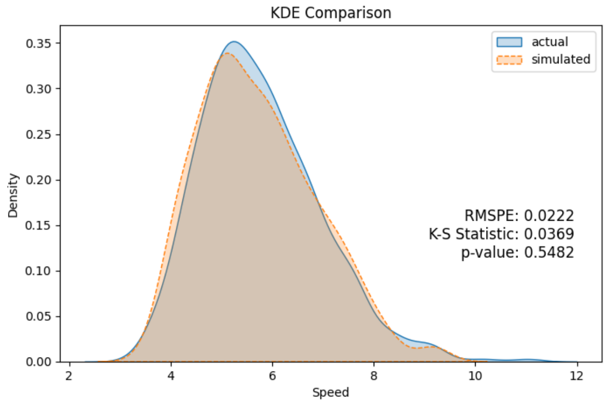

Figure 6: KDE comparison of actual vs simulated speeds with with solutions from calibration 4

The RMSPE was reduced from 12% to around 2%. Additionally, the p-value from the KS test indicated that all four solutions produced simulated speed distributions that closely matched the actual speed distribution. The first solution performed the best in terms of p-value, while the third solution had the lowest RMSPE value. Although the RMSPE values were not significantly different, the p-values showed more variation. Visual validation of the simulations for all four solutions revealed good consistency.

Tau was calibrated to a lower value than the default, increasing acceleration. In crosswalks, pedestrians tend to walk faster due to higher motivation to cross quickly. Higher values of **ASocIso, BSocIso, ASocMean,** and **BSocMean** increase the repulsive force between pedestrians, reducing density. Except for **BSocIso**, all three were lower than the default in three out of four solutions. **Lambda** was higher than the default in most cases, reducing anisotropy. Lower anisotropy counteracts the stronger frontal repulsion, improving counterflow efficiency—an expected behaviour in crosswalks. A lower **VD** causes pedestrians to avoid opposing flow less; it was calibrated lower, further reflecting natural crosswalk behaviour.

When comparing the results with those of a similar study [22], the changes from the default values are consistent, except for the parameter VD. Additionally, the values of the parameters Tau, ASocIso, and BSocIso exhibited smaller changes compared to the similar study.

The calibration results with different seed values were not highly consistent. It can be attributed to the fact that only average crossing speeds were used for calibration, and all pedestrians were treated as a single type, which did not fully capture the complexity of pedestrian behaviour.

4. Conclusion

The study aimed to establish pedestrian simulation study in Nepal by calibrating the Social Force Model (SFM) parameters in VISSIM. In a case study of a signalised crosswalk on Madan Bhandari Road, near Civil Service Hospital, Kathmandu, a genetic algorithm was used to fine-tune the SFM parameters. The simulated speed distribution significantly aligned with the observed speed distribution, as evidenced by reduced Root Mean Square Percentage Error (RMSPE) values and higher p-values in the Kolmogorov-Smirnov test. The calibrated parameters reflected natural crosswalk behaviour and simulation using those parameters were visually valid too. This successful calibration of SFM parameters in popular simulation software VISSIM provides a realistic model for pedestrian behaviour in Kathmandu. Also, the changes from the default values were found to be consistent with those observed in a closely related study.

Moreover, this research lays the foundation for further studies on pedestrian movement in Nepal and highlights the potential of VISSIM as a powerful tool for urban mobility analysis, which has been underutilised for pedestrian simulations in the region. However, a limitation of this study is that only average crossing speeds were used for calibration, and all pedestrians were treated as a single type, which did not fully capture the complexity of pedestrian behaviour.

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