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Calibrating the Highway Safety Manual Predictive Models for Multi-lane Rural Highway Segments in Saudi Arabia

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Abstract

Crash prediction models (CPM) are mostly used for network screening in the road safety management process. The Highway Safety Manual (HSM) offers consistent and reliable CPMs for various roadway facilities that are commonly known as safety performance functions (SPFs). SPFs are statistical regression models that estimate the expected crash frequencies by crash severity, type, and facility types as a function of geometric characteristics and traffic exposure. They are vital in identifying high-frequency crash locations and assessing the effectiveness of safety countermeasures. HSM SPFs were originally developed using data collected from a selected few states in the US. When applied to different jurisdictions, agencies can either develop local SPFs or calibrate the existing HSM base SPFs for local conditions depending on various trade-offs. This study aims to calibrate HSM-default SPFs for multi-lanes rural divided highway segments using three years of crash data (2017-2019) in the Kingdom of Saudi Arabia (KSA). In this regard, two highways (NHWY-80 and NHWY-85) in the eastern region were considered for the analysis. Crash and traffic were procured from the MOT (Ministry of Transport), Riyadh, KSA. Geometric data was from MOT as well as google earth and field surveys. Calibration procedure as recommended by HSM was followed to obtain the local calibration factors. The Interactive Highway Safety Design Model (IHSDM) calibrator tool was for the analysis. SPFs calibration results revealed that HSM predictive methodology consistently overpredicts all types of crashes (i.e., total, fatal and injury, and property damage crashes) on both highways. The estimated calibration factors ranged from 0.53 to 0.78. Various goodness of fit (GOF) measures (like MAD, MSPE, MPB) were used for quality assessment of calibrated SPFs. Methods used in this study could be beneficially practiced in any jurisdiction. Calibrated SPFs provide a favorable alternative and replacement of HSM-default SPFs, thereby making the crash predictions more accurate and helping in better decision-making related to highway safety.

Keywords: Highway Safety Manual; Safety Performance Functions; Multi-lane rural highway segments; Calibration Factors; Goodness-of-fit measures.

1. Introduction

Road traffic crashes have become a threatening public health concern worldwide. Estimates suggest that globally around 1.35 million people lose their lives, while nearly 50 million suffer injuries in road traffic crashes [1]. The resulting economic consequences are thought to be over USD 520 billion worldwide [1,2]. Low-and-middle income countries carry 90% of the total road fatalities [3]. In general, the Gulf Cooperation Council (GCC) countries are facing serious road safety issues due to the rapid motorization following tremendous economic growth during the past few decades. Compared to the US and Europe, the fatality rate is significantly high in GCC countries. According to the latest global status report on road safety published by the World Health Organization (WHO), the fatality index (deaths/100K population) in the Kingdom of Saudi Arabia is approximately 27, which is among the worst compared with neighboring GCC nations [1]. Traffic collisions account for around 4.7% of total mortalities in KSA [4]. Different regions in the country have witnessed the crash to injury ratio varying between 8:4 to 8:6, which are very significantly high compared to the global average value of 8:1 [5,6]. Due to traffic crashes, economic losses account for approximately 4.3% of the Kingdom's GDP [7]. In recent years, several studies have attempted to investigate the crash causation and injury severity risk factors in KSA. The literature suggests that factors such as overspeeding, distracted driving, non-compliance with traffic rules, and aggressive driving are the few predominant factors responsible for increased crash incidence and severity [7–11]. Traffic-related injuries are the leading cause of death among the young Saudi population, which is a worrying situation. Recently, national and provisional authorities have initiated various efforts (installation of SAHER and traffic enforcement schemes, imposition heavy on violators, child restraint law, regular safety training and awareness campaigns, routine maintenance on highways, etc.) to curb road safety issues. However, there is no significant improvement in the road safety situation.

Identification of hazardous road segments/sites is an integral component of effective road safety management. It can also help in the selection of appropriate countermeasures, thereby optimizing the use of road maintenance budget and resources. One of the primary goals of road safety studies is to understand and quantify the safety effectiveness of various countermeasures and their relative significance for better decision-making. CPM are useful tools for -detecting critical locations where the odds of crash risks are high [12]. In 2010, following extensive research in road safety and its practices in the past few decades, AASHTO (American Association of State Highway and Transport Officials) published Highway Safety Manual (HSM). Part C of HSM covers predictive methodologies that help to estimate the expected number of road traffic crashes along various highway facilities, for example, rural two-lanes two-way highways, urban arterials, sub-urban arterials, and rural multilane highways. In 2014, an appendage to the first edition of HSM was published covering freeways and ramp segments.

The procedure of predictive methods given in Part C of HSM involves the application of statistically derived regression models, commonly called safety performance functions (SPFs). To develop jurisdiction-specific SPFs, two main statistical modeling approaches, i.e., negative binomial (NB) and Poisson have been widely used [12–14]. The main purpose of SPFs is to quantitatively correlate the expected mean number of yearly crashes with geometric characteristics and traffic exposure of a highway. HSM SPFs have been developed for a set of base conditions (unique to each facility type) using limited data collected from a few selected states in the US. It is essential to modify crash estimates obtained by SPFs, which can be done using various crash modification factors (CMFs). This modification is necessary for adjusting the multiple changes in the site's geometry under certain non-base conditions [15]. For example, a lane width of 12 feet indicates a base condition in a sample CMF calculations for a rural multilane highway. If the highway segment's lane width is less than this value, it needs to be adjusted for SPFs for correct estimations by applying appropriate CMF for lane width. Similarly, suitable CMFs for other non-base conditions (such as median width, shoulder type, and width, lighting conditions, enforcement, etc.) must be computed to improve SPFs crash predictions.

This paper demonstrates the applicability of the HSM calibration procedure for developing SPFs calibration factors for multilane rural highway segments in KSA. HSM SPFs are calibrated for total, FI (fatal and injury), and PDO (property damage only) crashes for the study area. To investigate the quality assessment of the calibration process, several performance statistics such as MAD, MPB, and MPB, etc., are used. The calibration dataset includes crash, traffic, and geometric data for two multilane rural highway segments (NYWY-80 and NHWY-95) in the eastern province, KSA. Rural highways in KSA account for a significant proportion of total traffic fatalities. At the time this study was launched, no study had been performed on the calibration of HSM crash prediction models for rural multi-lanes highways, for GCC countries in general, and KSA in particular.

2. Literature Review

2.1. Importance of HSM Calibration

A detailed review of the existing literature suggests that three main approaches are used to calibrate HSM SPF. To compute the local calibration factors, the first method accounts for differences between the local jurisdiction and jurisdiction for which base SPFs in HSM were developed. The second method develops SPFs with available data for jurisdiction under consideration. The third method uses specific default parameters of SPFs in HSM in the absence of any associated information. However, the use of the third method is criticized as it could introduce some biases in SPF calculation. Factors commonly associated with crashes such as topography, animal population, weather conditions, highway conditions, lighting crash-reporting thresholds vary from one state/jurisdiction to another. Applying HSM base SPFs to other jurisdictions can lead to biased crash predictions. Therefore, it is highly recommended to either calibrate default SPFs or develop jurisdiction-specific SPFs to avoid this issue [16]. Agencies could either calibrate the HSM predictive models using adjustment factors by ranges of exposure variables (local traffic, road inventory, and crash data) or develop jurisdiction-specific models. In deciding on which approach to undertake, different trade-offs are involved, such as data availability, accuracy, data collection requirement, data processing, the minimum sample size for analysis, modeling and statistical expertise, the labor involved, and reliability of estimates. Limited data in developing countries is the main hindrance to develop jurisdiction-specific crash prediction models. Though developing jurisdiction-specific SPFs is more preferable, a valid alternative to developing them is to calibrate existing SPFs. [12,17]. As road safety conditions fluctuate over time, transport agencies should use calibrated HSM predictive models.

The benefits of developing local safety performance functions (SPFs) in the first place are unclear and may vary from location to location [15]. As the HSM SPFs are already established and are based on comprehensive data and decades of research, jurisdictions are encouraged to calibrate the HSM-default SPFs and perform the quality assessment of calibrated HSM-default SPFs prior to developing local/jurisdiction-specific SPFs [18]. WHO has also emphasized the priority of adapting propitious and established methods from developed countries to developing countries and assessing their effectiveness in local contexts [19,20]. Often there are some similarities between countries in terms of contributing factors and crash mechanisms despite the general differences in terms of overall crash rates. Thus, there is a certain appeal in investigating the transferability of established methods from developed countries to developing nations, particularly under circumstances where conditions do not favor the development of regional crash prediction methods. Calibration is defined as the process of correcting the HSM base-SPFs to reflect local traffic conditions. Calibrating HSM predictive models aims to achieve reliable and realistic and crash estimates and avoid biased crash predictions.

The model transferability of HSM has become much simpler with the advancement of the latest statistical techniques and new software application tools. As a decision-making tool, implementing HSM predictive models to developing countries could provide a more cost-effective approach to transport agencies and government authorities to efficiently utilize limited resources. The application of calibrated HSM SPFs will help to prioritize engineering alternatives and safety planning based on their potential safety effects. To conclude, it may be argued that borrowing HSM SPFs and calibrating them to local conditions could curtail the expenses of labor resources and capital costs (required for data collection and hiring the experts for data processing) significantly relative to developing the models. Another motive of using the calibrated HSM SPFs is the amount of time saved in the process. A recent study reported that man-hours invested for data collection and preparations for developing SFPs are three-fold of those needed for calibrating adopted SPFs [18].

2.2. Review of Past Studies

In literature, limited studies have attempted to calibrate SPFs for local traffic exposure and geometric conditions [18,21–26]. Sun et al. were the first to perform the study to calibrate HSM CPM for rural two-lane roadway segments in Louisiana [27]. The authors followed the calibration procedure recommended by HSM. Study results demonstrated that calibrated models performed reasonably well compared to base CPM. Another study conducted by Sun et al. focused on calibrating SPFs for rural multilane highway segments [28]. The authors also investigated how calibrated models could be used for network screening and identification of plausible problems with application. Srinivasan and Carter selected various types of two-lane two-way rural highways utilizing different crash-reporting databases in North Carolina to developed SPFs [29]. Calibration factors for total crashes were computed using HSM prediction methods. Later on, Smith et al.

conducted a study for the recalibration the SPFs developed earlier by Srinivasan and Carter in 2011. Recent crash data from the study area was used for recalibration [30]. Xie et al. also conducted SPFs calibration analysis for various two-lane, two-way roads rural highway facility types in Oregon [31]. The final calibration factor of 0.74 indicated fewer predicted crashes compared to observed crash frequencies. The authors argued that lower calibration value might be associated with non-reporting of property damage only (PDO) crashes in the state. Mehta and Lou examined the applicability of HSM predictive models to Albama data [32]. The study also developed state-specific models for four-lane divided rural highway segments and two-lane, two-way highways. Jurisdiction-specific SPFs were developed by using NB and Poisson models. The resulting calibration factors estimated using NB methods were 1.522 and 1.863 for two-lane two-way rural highway segments and multilane divided highway facilities.

In their study, Brimley et al. also calibrated for two-lane two-way rural highway segments in Utah employing hierarchical Bayesian and NB modeling techniques [33]. Hierarchical Bayesian was found more useful in identifying the unsafe segments. HSM SPF calibration factor was computed to be 1.16, suggesting underprediction of the base model. Jalayer et al. introduced a modified methodology to estimate calibration factors considering the recent crash recording threshold (CRT) for five different urban and suburban highways in Illinois [34]. Study results showed that the higher the CRT corresponds to fewer PDO crashes. The calibration factors were reduced from 0.68 to 0.55 before and after the implementation of CRT change, respectively. A study performed by Srinivasan et al. calibrated and developed HSM prediction models for the state of Florida [35]. This study compared calibrated factors developed for different highways with HSM equations. Sun et al. recently conducted a study to calibrate HSM base SPFs to four-lanes urban and rural freeway segments and six-lanes urban freeways using three years of crash data

(2009-2011) in Missouri [36]. Estimated calibration factor values for PDO crashes were higher than fatal and injury (FI) crashes for all the considered freeway types. The authors performed a follow-up study in 2018 to recalibrate all the previous freeway facilities and segments using the recent 2012-2014 crash data [37]. The newly estimated calibration factors had minor variations from the previous calibration for some facility types. Authors reported that these changes might be attributed to crash reporting differences, driver behavior changes, and natural variability in the data. In another study, Shin et al. utilized Maryland crash data (2008-2010) to calibrate freeway segments, ramp terminals, and speed-change lanes [38]. They calculated the calibration factors using the IHSDM tool developed by FHWA (Federal Highway Safety Administration) [39]. Results showed that HSM predictive models overestimated both PDO and FI crashes mostly for ramp and freeway facilities. Dutta et al., in their study, demonstrated that crash prediction based on disaggregated traffic flow state information is more rational, accurate, and robust compared to those obtained for typically used average annual daily traffic exposure [40].

Williamson and Zhou documented the development of calibration factors for crash prediction models for rural two-lane roadways in Illinois [41]. They analyzed three years of crash data from 2007 to 2009 for randomly selected road segments meeting the HSM requirement. The three years of crashes were averaged and determined to be 34 per year, compared to the one year of predicted crashes. The under-predicted value of the estimated calibration factor of 1.58 for Illinois provides evidence that the crashes on Illinois rural two-way two-lane roadway segments are higher than the national average. Llopis-Castelló and Findley deployed aggregated and disaggregated analysis to study the influence of different calibration factors on crash prediction in North Carolina [42]. Their study recommended that different calibration factors should be used for different road segments and crash severity types. The predicted calibration factor for horizontal curve and tangents was 1.57 and 1.15, respectively, while the calibration factor for all types of roads was 1.34 for North Carolina. Another study by Shin et al. computed Maryland-specific local calibration factors (LCFs) to apply the predictive models in HSM's using crash data sets of in-state roadways from 2008 to 2010 [43]. They reported that LCFs for most of the intersections of Maryland were less than 1.0, and some were as low as 0.5. This overprediction by the model shows that none of the intersection facilities reached 50% of the crash predicted threshold. However, they also articulated some limitation of the study that there were lack of sample data in some segments, exclusion of some important cities of the state and chance of missing PDO reports as reporting is self-volunteered if no injury is involved.

The calibration methodology presented in Appendix Part B of HSM was used by Berry et al. to compute the calibration factors for a six-lane urban freeway in Missouri [44]. The study utilized the 2012-2014 crash data from the study area. It was found that HSM methodology overpredicted all single-vehicle FI and PDO crashes and underpredicted multiple-vehicles PDO crashes. Vargas et al. compared the Florida-specific SPFs and the calibrated SafetyAnalyst SPFs to predict crashes on urban and rural multilane and two-lane highways [15]. The main aim was to assess if the jurisdiction-specific SPFs are warranted for the considered facilities. Study results showed that jurisdiction-specific SPFs showed a better fit compared to calibrated SafetyAnalyst-default SPF to the local data. A recent study by Carlos et al. concluded that crash prediction accuracy was slightly improved by calibration function compared to that obtained from calibration factors [45]. In another follow-up study, Carlos et al. compared the performance of calibration factors, functions, and jurisdiction-specific models in predicting the expected crash frequencies on urban four-lane freeway segments in Missouri [46]. The authors used different goodness of fitness measures such as cumulative residual plots, log-likelihood, and inverse overdispersion to compare the performance of each predictive approach. Calibration of AADT ranges performed better than all other calibration functions and factors proposed in the study. In their study, Karmacharya et al. calibrated the HSM base-SPF for various urban and suburban intersections (3SG, 4SG, 3ST, and 4ST) in Kanas, the US [47]. Results showed that the HSM methodology overpredicted the crashes at all types of intersections except 4SG, where the average calibration factor was 1.17. This study also compared the reliability of calibrated SPFs with locally developed SPFs through cumulative residual plots and coefficient of variation. The analysis revealed that calibration functions have better reliability compared to the developed calibiration factors for all intersection types.

Shin et al., in their recent study used HSM calibration methodology to examine the adequacy of the calibration process to freeway segments, ramp terminals, and speed-change lanes in Maryland [48]. Local calibration factors (LCFs) developed for each facility type were less than 1 implying the overprediction of applicable HSM predictive models. Another HSM calibration study considered a total of 1,133 freeway segments in the state of Kanas in the US and concluded that HSM predictive methodology consistently underpredicted all PDO crashes and overpredicted all FI crashes [49]. Sacchi et al. assessed HSM's transferability to highways and validated the performance of jurisdiction-specific models using cumulative residual plots in Itlay [50]. Matarage and Dissanayake used the Kansas freeway data to evaluated the performance of calibrated HSM-base SPF and calibration functions [51]. The dataset was limited to freeway segments, merging and diverging lanes only. Empirical results showed that the calibrated HSM base SPFs is not appropriate for all of the considered locations; instead, the calibration function performed better to the dataset. In another study, the authors compared the predictive performance of calibrated SPFs and calibration functions for 74 signal controlled ramp terminals and 120 cross-road stop controlled ramp terminals using three-year crash data (2014-2016) from Kanas [52]. Though the calibration factors estimated for ramp terminals showed satisfactory results, calibration functions yielded better-fitted models than local data. Moraldi et al. investigated the transferability of the HSM predictive method to two-lanes, two-way German highways [53]. The calculated calibration factor of 0.94, which is close to 1.00, approves the HSM predictive model's adequateness for the German highways. It may be noted from the literature aforementioned that the adequacy of HSM predictive models has been investigated for various facilities types across different jurisdictions within and outside the US. However, there are very limited similar studies conducted in GCC countries, despite the fact these countries are facing serious road safety challenges. In KSA, a single study on the topic was performed by Kaaf and Abdel-Aty to examine the calibration of SPFs on urban four-lane divided roadway segments in Riyadh [54]. In Riyadh, jurisdiction-specific SPFs provided the best results to predict severe crashes. The study concluded that Riyadh's local CMFs outperformed the calibration method using HSM default values.

3. Data and Methods

3.1. Study area and routes Selection

Two inter-city highways were selected for SPFs calibration, i.e., routes 80 and 85. The National highway-80 (NHWY-80) connects KSA's capital city of Riyadh to Dammam in the eastern province, while the highway-85 (NHWY-85) links the cities of Dammam and Hafr Al-Batin. The primary motive for selecting these routes was the availability of the required data to accomplish the research objective. NHWY-80 has a length of approximately 255 miles, of which a significant part (>90%) runs through plain and desert terrain. Similarly, NHWY-85 has a length of about 300 miles, passing through the town of Nairyah. Both the highways are rural multilane (having three lanes in each direction for most stretches) with dividing medians to separate the opposing traffic. Both the highways carry mixed traffic, which comprises light vehicles and heavy vehicles. Ruling design speed along both highways is predominantly 140km/hr, with few stretches having a limiting speed of 120km/hr. Figure 1 shows the study sections along both highways.

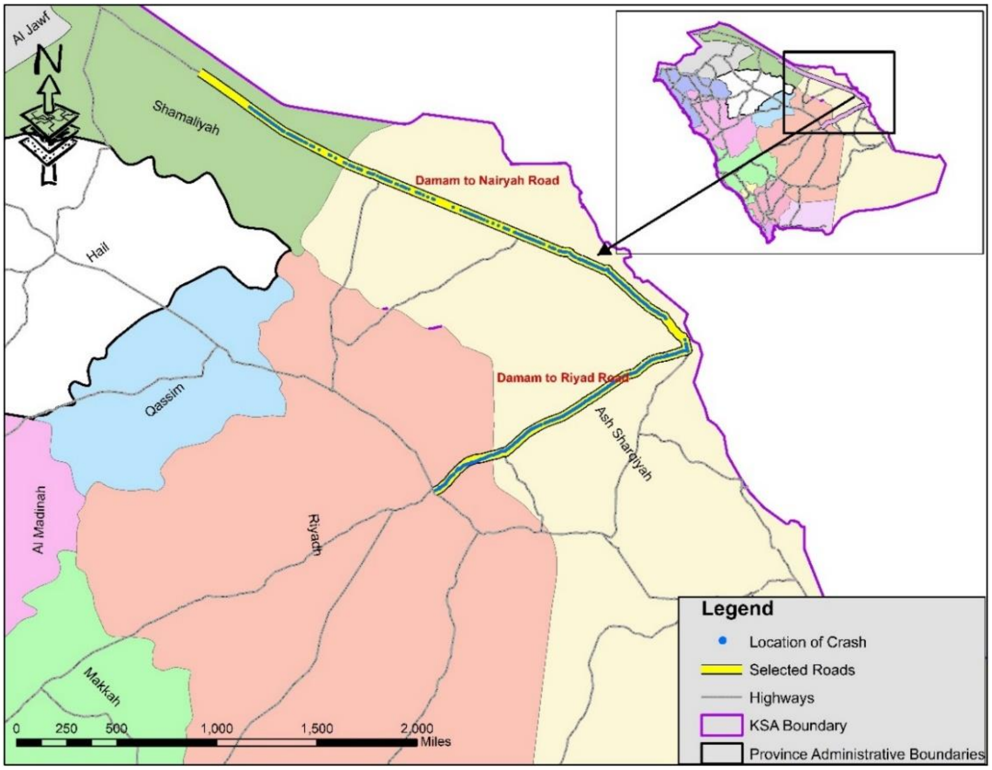


Figure 1. Study area route map for NHWY-80 and NHWY-85

3.2.Segment reduction

To apply the HSM calibration procedure, the highway must be divided into individual sites, having homogeneous roadway segments or intersections. Some of the key criteria for obtaining homogenous segments include traffic volumes (AADT) and road inventory data (number of lanes, lane width, type and width of shoulders and medians, presence of lighting, automated speed enforcement, etc.). For SPFs predictive model calibration, HSM recommends using a sample size of 30-50 sites comprising at least 100 crashes per year along with the entire facility. It also recommends a minimum segment length of 0.1mi for each segment. To avoid any bias in site selection, it is also suggested to choose the sites randomly without considering the crash frequency during the observation period. [55]. As a result, the dataset may comprise sites with high number of crashes, as well as some will have with no crashes. However, recent studies have reported that HSM suggested sample size is arguable; for example, it may be challenging to obtain 100 crashes from 30-50 sites in some instances [16,31]. On the other hand, few studies suggested that a single criterion in HSM SPFs calibration procedure might not be practicable for sample size selection since different highways have diverse homogeneities and characteristics [56–58]. For the current study, the ET Geo Wizards Spatial Analytic Tool in ArcGIS was used to segmentation the study section along both highways following the procedure of previous studies [49,59]. Only tangent segments were excluding rest areas, and interchanges were included in the analysis. Using the criterion mentioned above, the study section of NHWY-80 was divided into 30 segments having an average length of 4.77 miles with a standard deviation of 3.76 mi (Table 1). Similarly, NHWY-85 had a mean segment length of 11.10 miles with a standard deviation of 6.40. Figure 2 shows the three-years (2017-2019) average crash frequencies at study segments on both highways. Total crashes for both highway segments exceeded as per the HSM requirements.

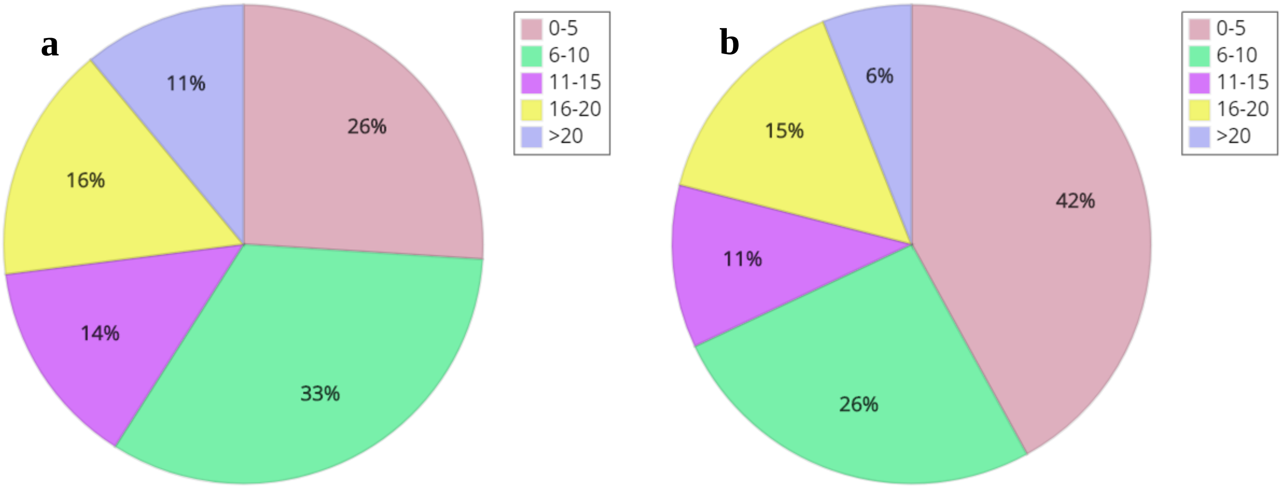


Figure 2. Three-year average crash frequency on the study segments: a) NHWY-80, b) NHWY-85

3.3.Data Collection

Accurate calibration of SPFs is dependent mainly on the quality data used utilized in the process. Two types of data are required for the SPFs calibration process—first, a detailed historical crash (minimum of three years) at the interest sites; second, datasets for road inventory and condition are also needed. This includes geometry, traffic volumes, and physical feature within the highway's right-of-way. As recommended by HSM, the calibration period should be a multiple of 12 to avoid any seasonal effects. However, the HSM does not provide detailed guidelines for collecting the essential data desired for SPFs calibration [60]. Table 1 presents the data needs for calibrating HSM SPFs to multilane rural highway segments, together with their source of collection/extraction. It also summarizes the key descriptive statistics of traffic and road geometry data of study segments for both the highways. This research utilized the traffic crash data obtained from the Ministry of Transport (MOT) traffic safety department in Riyadh, KSA. The data covers all types of motor vehicle crashes that occurred in the study area from January 2017 to December 2019. The crash contains information on crash locations (with precise latitude and longitudes information), date and time of the crash, weather conditions, road surface condition, lighting conditions, crash cause, collision type, vehicle characteristics, etc. Crash injury severity is reported in three categories: fatal (F), injury (I), and property damage only (PDO). Table 2 shows the distribution of crash frequencies and the share of each injury severity group across different years for study sections of both highways. A total of 998 and 729 crashes occurred on study sections of NHWY-80 and NHWY-85, respectively. PDO crashes dominate a large proportion of reported crashes along both highways. NHWY-80 segments had a mean crash frequency of 11.09, with a standard deviation of 6.80. Similarly, for NHWY-85 segments, the average and standard deviation of crash frequencies were 6.45 and 3.98, respectively. Traffic volume data (AADT) for the analysis period were also obtained from MOT. Besides, the needed road geometry data were mostly extracted using the google earth pro tool, while for a few locations, it was collected from MOT where available.

Table 1. Summary of road geometry, crash data, traffic volumes, and data sources for selected routes

Data type	**NHWY-80** (*N=30*)				**NHWY-85** (*N=38*)				**Data Source**	**HSM Base Condition**
	Min.	Max.	Mean	SD	Min.	Max.	Mean	SD		
Segment Length (mi)	1	21.40	4.77	3.76	4.20	36.60	11.10	6.40	Google Earth	Need actual data
Lane Width (ft)	11.48	12.60	12.08	0.34	11.46	12.79	12.03	0.33	Google Earth/ MOT/ Survey	12
Shoulder width (ft)	8.66	13.10	6.07	1.84	6.66	13.12	9.08	1.60	Google Earth /MOT/Survey	8
Median Width	39.37	70.54	57.60	7.85	37.40	82.03	61.77	13.80	Google Earth/ MOT/ Survey	30
Crash Data (2017-2019)	2	53	11.09	6.80	2	27	6.45	3.98	MOT	Actual crash record
ADDT (veh/day)	11263	28145	17557	5294	4655	6849	5251	681	MOT	Need actual data
Presence of Lighting	NO	NO	NO	NO	NO	NO	NO	NO	Google Earth/ MOT	Assume no lighting
Automated Speed Enforcement	Present	Present	Present	Present	Present	Present	Present	Present	MOT	NOT Present

Table 2. Crash severity descriptive statistics for the study stretches

Time Period	**NHWY-80**			**NHWY-85**		
	Total	Fatal and Injury	PDO	Total	Fatal and Injury	PDO
2017	388	180	208	301	133	168
2018	334	141	193	231	113	118
2019	276	116	160	197	88	109
Grand Total	998	437	561	729	334	395
Share (%)	100	43.79	56.21	100	45.82	54.18

3.4.Calibration Procedure

Safety performance functions (SPFs) in the HSM were initially developed using data for jurisdictions and periods rather than when and where they should be utilized. When applied to different jurisdictions over different time periods, it is essential to calibrate SPFs to account for differences due to spatial and temporal trends. Because the HSM SPF holds the most weight in crash prediction, their calibration is more critical and efficient than other adjustments. HSM predictive models follow a three-step procedure to predict the expected number of crashes for a given facility type (road segments, intersection, etc.). The steps involved are i) computing SPFs under the base conditions, ii) determining the crash modification factors (CMFs) to account for variations from base conditions, and iii) finding the calibration factor C as an ultimate adjustment for all other differences, whether measurable or immeasurable, known or unknown, such as crash reporting system procedures, crash recording threshold (CRTs), driver and animal populations, climate, etc. The HSM predictive models take the following general form (equation 1) to yield the average crash frequency on divided and undivided multilane highways.

$$N_{predicted,i(unadjusted)} = N_{SPF,i} \times (CMF_{i1} \times CMF_{i2} \times CMF_{i3} \ldots \times CMF_{ij}) \quad (1)$$

Where;

Npredicted,i = predicted average crash frequency for a specific year on i^{th} site

$N_{SPF,i}$ = total predicted crash frequency for a specific year on i^{th} site under the base condition

CMF_{ij} = crash modification factors pertaining to specific safety issue j on i^{th} site

CMFs are the multiplicative factors used to evaluate the crash impact of road geometric conditions. For instance, under base conditions for rural multilane highways (shown in Tables 3 and 4), CMFs values are equivalent to 1. A segment with 14 feet of lane width, and the right shoulder width less or greater than 8 feet represents a deviation from base conditions, and thus CMFs will be adjusted based on guidelines provided by HSM. A CMF value greater than 1 indicates a higher expected average crash frequency compared with SPF base conditions, while the CMF value less than 1 shows a reduction in average crash frequency estimates. The predicted average crash frequencies obtained from equation 1 does not provide accurate estimates as additional adjustments may be essential to adjust for local conditions. A calibration factor should be included in the calculations to enhance the accuracy and reliability of predicted crash estimates for a given jurisdiction. This leads to a modified predictive model (shown in equation 2) that applies to all facility types cover SPFs developed for base conditions

$$N_{predicted,i(unadjusted)} = N_{SPF,i} \times (CMF_{i1} \times CMF_{i2} \times CMF_{i3} \ldots \times CMF_{ij}) \times C_i \quad (2)$$

Here C_i denotes the calibration factor for the ith site. SPFs for predicting the expected average crash frequency as a function of exposure (traffic) and roadway characteristics on rural divided highway segments is given by relation shown in equation 3.

$$N_{SPF,(rd)i} = e^{(a+b\times\ln(ADDT)+\ln(L))} \quad (3)$$

Where,

$NSPF_{,(rd)i}$ = total average expected average crash frequency of i^{th} roadway segment per year,

ADDT = average annual daily traffic in veh./day (both directions) on i^{th} roadway segment in the corresponding year,

L = length of i^{th} roadway segment per year in miles (mi),

a,b = regression coefficients

The SPF for rural multilane highways shown above applies to AADT ranging between 0 to 89,300 veh/day, beyond which it may not provide reliable prediction results. The over-dispersion parameter associated with SPF is computed in terms of the function of segment length and is given by equation 4.

$$k_i = \frac{1}{e^{(c+\ln(L_i))}} \tag{4}$$

Where,

ki = overdispersion parameter associated with the i^{th} roadway segment,

L = length of i^{th} roadway segment per year in miles (mi),

c = regression coefficient for determining the overdispersion parameters

The procedure for calibrating the SPFs given in Part C of the HSM was followed (AASHTO, 2010). Figure 3 presents the stepwise methodological framework for computing the local calibration factors for multilane rural highway segments in the study area. HSM predictive model calibration is a five steps procedure given below: i) identification of desired facility type (such multilane rural highways considered for this study), ii) selecting sites/segments for calibration, iii) collecting the required crash data and roadway condition data for selected sites, iii) apply applicable HSM predictive model (equation 3) to obtain the expected crash frequencies per year at those sites, and v) compute the calibration factor using equation 5.

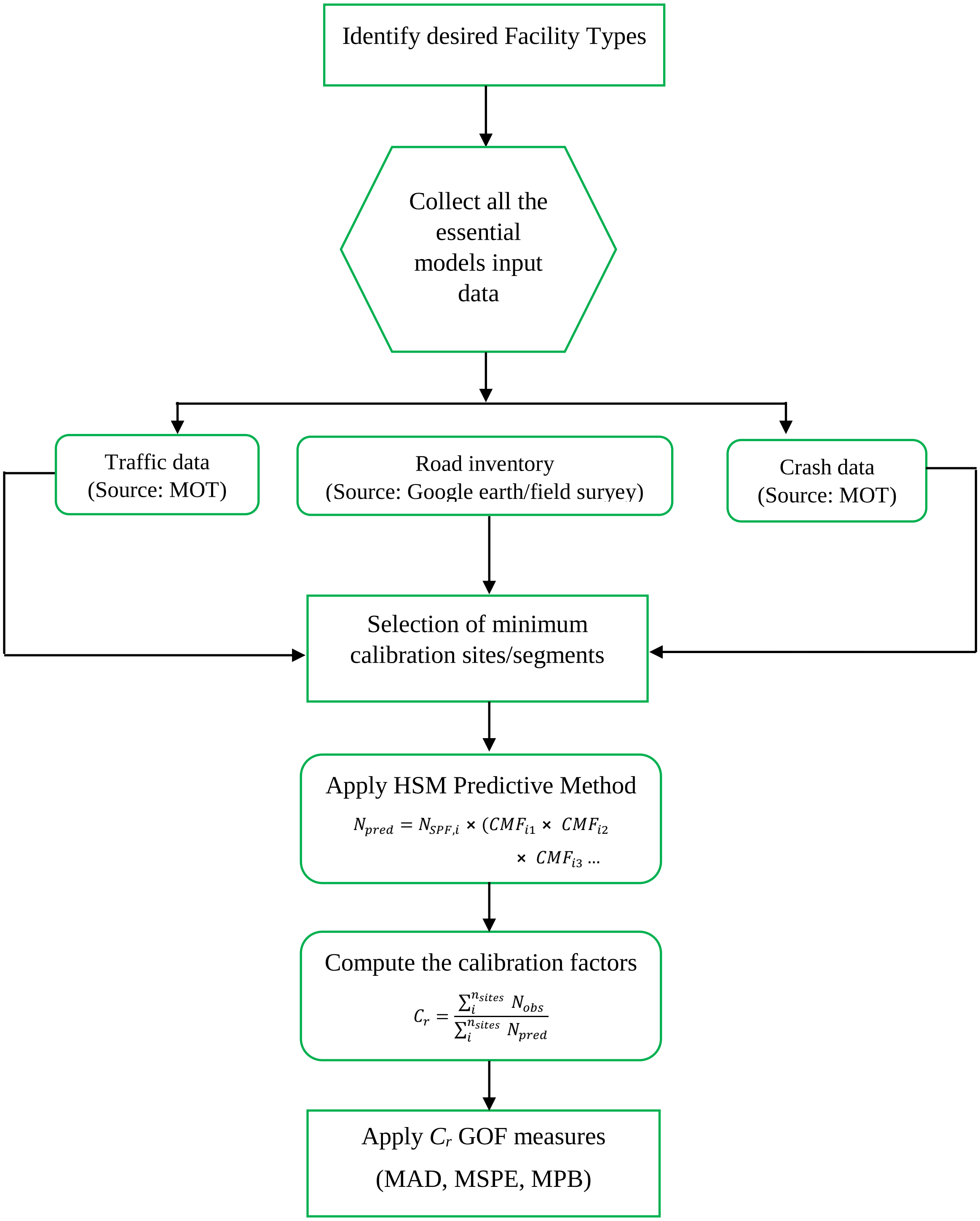


Figure 3. Flowchart for the methodological framework

$$C_r = \frac{\sum_i^{n_{sites}} \sum_j^{m_{years}} N_{observed}}{\sum_i^{n_{sites}} \sum_j^{m_{years}} N_{predicted(unadjusted)}} \quad (5)$$

All the variables are the same as explained previously. A Cr value of 1.0 indicates that HSM-SPF overpredicts the mean crash frequencies. This implies that multiplying the calibration factor under base conditions will lower the predictions to match observed mean crash frequencies. While a Cr value greater than 1.0 means that HSM-SPF underpredicted the crash frequencies. In this situation, multiplying the factor increases the predictions to match the observed frequencies on average. Several software support packages have built-in calibration capabilities for different HSM predictive models. This study one such calibrator tool commonly known as IHSDM (Interactive Highway Safety Design Model) for calibrating the HSM base SPFs. In addition to calibration, crash type distribution, and crash severity, the software allows the state agencies to develop and implement jurisdiction-specific SPFs [61].

3.5. Goodness of Fit Measures

Three commonly reported goodness of fit measures of SPFs were used, i.e., mean absolute deviation (MAD), mean square predicted error (MSPE), and mean prediction bias (MBP). MAD was suggested by Washington et al. for determining the adequacy of SPFs [62]. It measures the average magnitude of variability in the model. MAD can be computed as the ratio of the sum of the absolute difference between predicted mean values and observed crash counts at n number of sites. Smaller values of MAD are preferred over larger values. MAD can be calculated using equation 6 given below.

$$MAD = \frac{\sum_{i}^{n_{sites}} \sum_{j}^{m_{years}} \left| N_{SPF,i} - N_{obs,i} \right|}{n} \tag{6}$$

Where, $N_{SPF,i}$ is the predicted number of crashes on i^{th} segment, $N_{obs,i}$ is the observed number of crashes on i^{th} segment, n is the number of sites, and m is the number of years during the study period. Like MAD, MPB was suggested by Washington et al. that gives the direction and magnitude of average model bias compared to observed data. It is defined as the ratio of the sum of the predictive mean value minus observed crash count considering n number of sites. MPB can be calculated using equation 7. A negative value of MPB indicates that the SPF underestimates the mean number of crashes, whereas a positive value implies that the site is less safe than it actually is. If the model does not overpredict/underpredict the observations, MPB will be equal to zero. The only distinction of MAD from MPB is that positive and negative differences are unable to cancel each other out. Like MAD, Smaller values of MPB are preferred over larger ones.

$$MPB = \frac{\sum_{i}^{n_{sites}} \sum_{j}^{m_{years}} (N_{SPF,i} - N_{obs,i})}{n} \tag{7}$$

MSPE is defined as the squares sum difference between predicted and observed crash frequencies divided by the number of sites. This metric is used to assess the error associated with the external or validation dataset. A lower value of MSPE implies a better predictive performance of a model. MSPE can be computed using equation 8.

$$MSPE = \frac{\sum_{i}^{n_{sites}} \sum_{j}^{m_{years}} (N_{SPF,i} - N_{obs,i})^2}{n} \tag{8}$$

4. Results and Discussions

Calibration factors estimated for the study segments using the HSM calibration procedure are presented in Table 3-5. A calibration factor (Cr) value of 1.0 indicates that HSM predictive models accurately predict the expected average crash frequencies for a given jurisdiction, where Cr values of greater and less than 1 means that the default SFPS underestimate and overestimate the crash frequencies. The calibration factors are reported for total, fatal, and injury (FI) and property damage only (PDO) crashes in Table 3,4 and 5, respectively. Different goodness of fit (GOF) measures such as MAD, MSPE, and MPB are also calculated to show the adequacy and success of calibration. Considering the results in Table 3, it may be noted that both highways (NHWY-80 and NHWY-85) experienced a fewer number of observed total crashes compared with HSM predicted total crashes that resulted in small calibration factors. HSM overpredicts the total crashes by on average 29% and 35% on NYWY-80 and NHWY-85, respectively. GOF values show an acceptable and satisfactory model calibration process.

Table 3. Estimated calibration factors for total crashes

Analysis Period -	**NHWY-80**			**NHWY-85**		
	$N_{Observed}$	$N_{Predicted}$	Cr	$N_{Observed}$	$N_{Predicted}$	Cr
2017	388	471.52	0.82	301	409.12	0.74
2018	334	452.82	0.74	231	341.51	0.67
2019	276	489.56	0.56	197	376.69	0.53
2017-2019	998	1413.90	0.71	729	1127.32	0.65
Goodness of Fit Measures						
MAD		*5.13*			*4.41*	
MSPE		*208.30*			*143.14*	
MPB		*3.62*			*2.90*	

As shown in Table 4, the HSM predictive model again overestimates FI crashes. The HSM SPF estimated a total of 694.96 FI crashes over all the selected segments of NYWY-80 during the study period. There were only 437 observed crashes in this category. Using equation (5), the calibration factor for NYWY-30 was calculated to be 0.63. This value suggests that HSM SPFs overpredict the FI crash frequency by approximately 37%. Similarly, for NHWY-85, the HSM default predictive model estimated a total of 622.77 FI crashes, whereas the number of observed FI crashes were 334 only. The corresponding calibration factor was computed to be 0,53, which suggests that HSM overpredict the FI crash frequency by nearly 47%. Table 6 summarizes the calculations for obtaining the calibration factors for PDO crashes for the study area. As shown in Table 5, the observed and HSM predicted crashes for NYWY-80 are 561 and 718.93, resulting in a calibration factor value of 0.78. This means that the HSM default SPF predictive model for rural multilane highways again overestimates the PDO crashes by approximately 22%. Likewise, for NHWY-85, the observed and HSM predicted PDO crashes are 395 and 504.55 that yielded a calibration factor of 0.78, which is indicative of an overprediction of about 22%. Considering the GOF expressed in terms of MAD, MSPE, and MPB, it may be argued that PDO crashes had relatively less deviation between observed and predicted crashes, which produced better performance statistics compared to total and FI crashes. The highest discrepancy between HSM base SPFs and those calibrated to data for the study area occurs for FI crashes.

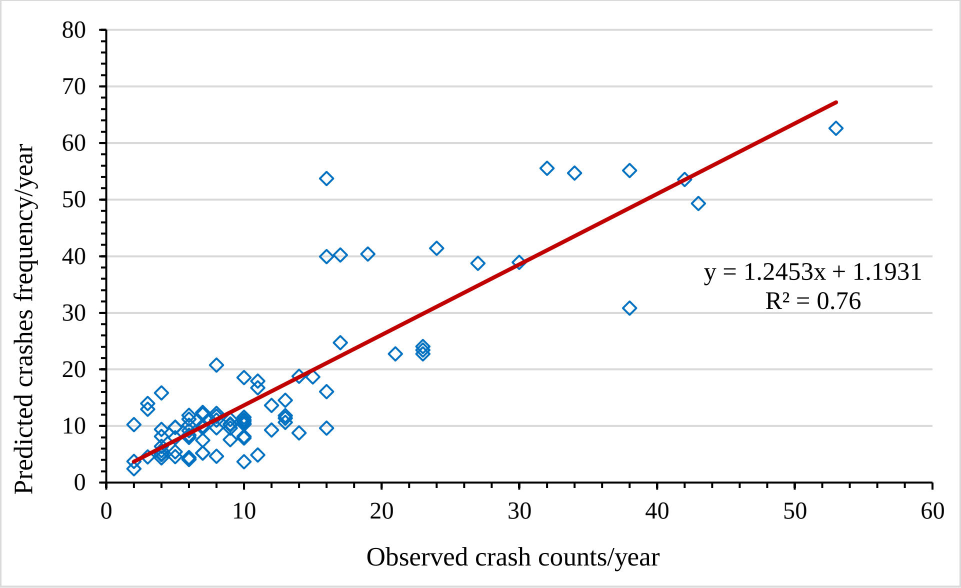
Table 4. Estimated calibration factors for FI crashes

Analysis Period	**NHWY-80**			**NHWY-85**		
-	$N_{Observed}$	$N_{Predicted}$	Cr	$N_{Observed}$	$N_{Predicted}$	Cr
2017	180	231.83	0.78	133	224.25	0.59
2018	141	223.20	0.63	113	190.35	0.59
2019	116	239.90	0.49	88	208.16	0.42
2017-2019	437	694.96	0.63	334	622.77	0.53
Goodness of Fit Measures						
MAD		*3.04*			*2.68*	
MSPE		*82.86*			*88.24*	
MPB		*2.86*			*2.53*	

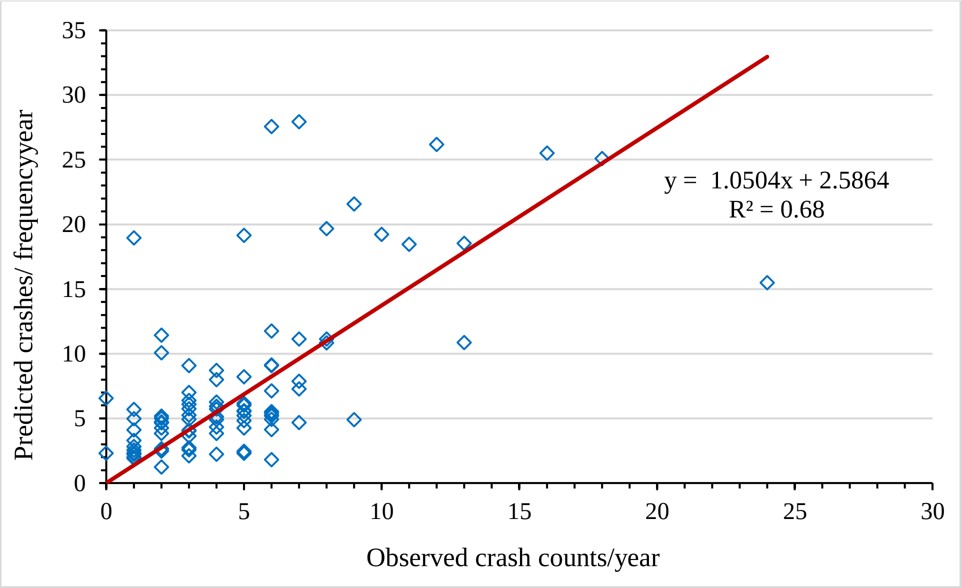
Table 5. Estimated calibration factors for PDO crashes

Analysis Period	**NHWY-80**			**NHWY-85**		
-	$N_{Observed}$	$N_{Predicted}$	Cr	$N_{Observed}$	$N_{Predicted}$	Cr
2017	208	239.68	0.87	168	184.86	0.91
2018	193	229.62	0.84	118	151.16	0.78
2019	160	249.62	0.64	109	168.52	0.65
2017-2019	561	718.93	0.78	395	504.55	0.78
Goodness of Fit Measures						
MAD		*3.33*			*2.24*	
MSPE		*82.27*			*45.12*	
MPB		*1.75*			*0.96*	

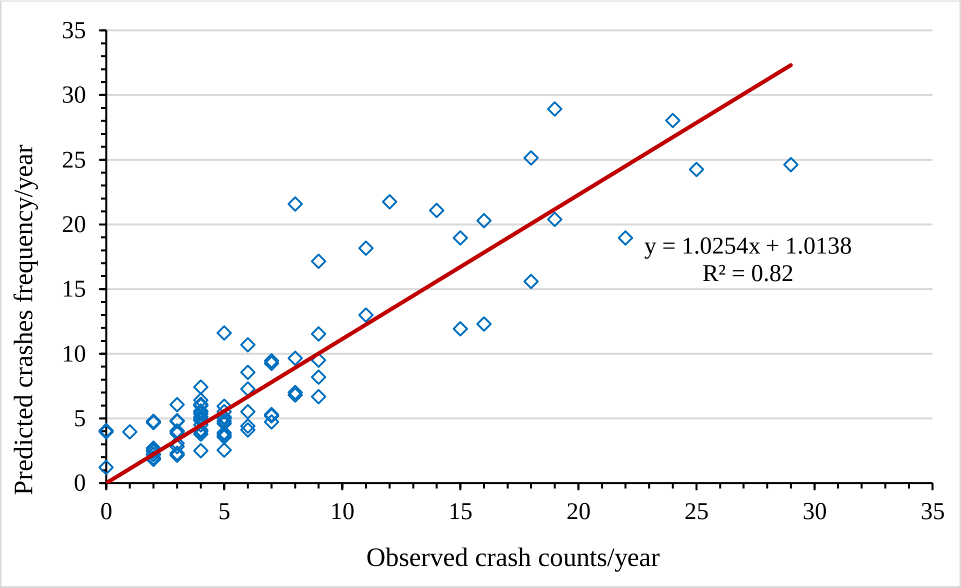
Figure 4 presents a regression plot to reflect the discrepancy between HSM predicted mean crash frequencies and observed crash counts for NYWY-80. Predicted versus observed crash plots are shown for each crash injury severity type (total, FI, and PDO). A regression equation, along with corresponding values of the coefficient of determination (R^2) is also provided for the subplot. The trend line shown shows the plot fit. If observed and predicted crash frequencies are identical, then R^2 will be 1.00. Whereas the values of R^2 below 0.60 indicate poor model fit. It may be noted from Figure 4 that the predictive performance of all models for various crash severity types is acceptable based on the model's R^2 metric. Among the three plots, the PDO plot for predicted crashes yields the closest crash estimations compared to observed PDO crashes.



(a)



(b)



(c)

Figure 4. Regression plot for observed versus predicted crashes: a) total crashes, b) FI crashes, c) PDO crashes

Globally, several studies have examined the international transferability of HSM predictive models to their local roadway and traffic condition. However, only a few studies have been carried out in the GCC regions in this regard. For example, A recent study compared the transferability of HSM SPFs, their calibration, and newly developed local SPFs for urban four-lane divided road segments in Riyadh, Saudi Arabia [54]. In their study, Asal and Said examined the transferability of HSM predictive models for multilane rural highway segments in the neighboring Gulf state of Egypt [63]. Study results showed that calibrated HSM SPFs overestimated the FI crashes by 4% and total crashes by 4% compared with 3% and 0%, respectively, for locally developed SPFs. In another study, Elagamy et al. investigated the effect of various segmentation procedures transferability of international SPFs for rural highways in Egypt [20]. The study reported that segmentation would influence the performance of the SPFs transferability process. Calibration factors for total crashes were less than 1, indicating that HSM predictive models were overestimating the crash frequencies on multilane rural highway segments in Egypt. Results indicated that jurisdiction-specific SPFs yielded a better fit for data utilized in this research. Feng et al. investigated the international transferability of freeways SPFs and their applicability for the identification of hotspots. The study utilized the data from two Chinese cities (Suzhou and Shanghai) and three US states (New York, Florida, Texas) [26]. Regardless of whether calibrated or uncalibrated, the transferability of SPFs between the two regions turned out to be unsatisfactory, mainly due to considerable variations in the traffic flow. A thorough comparative review of previous studies suggest that the application of HSM base SPFs are unsuitable for accurate crash predictions in other geographic location for a variety of reasons such as variations in climate, driving population, animal populations, crash reporting thresholds and procedures, etc. Uncalibrated models may lead to significantly erroneous crash estimation. These observations are further reinforced by the current study.

It may be concluded from the results reported herein that the application of HSM predictive models are unable to accurately estimate the crashes for rural highways in KSA. In general, calculated calibration factor values are much lower than 1.0, implying that HSM base SPFs are overestimating the mean crash frequencies on rural-multilane divided highways in the country. Therefore, HSM modified SPFs and the values of calibration factors reported in this study may be used for obtaining reasonably reliable crash estimates on other rural highways in the country having similar traffic and roadway conditions. Though this study used a sample size for each facility as recommended by HSM (30-50 sites), a larger sample size could result in better calibrations. By applying these calibration factors as per the recommendation of HSM, the overestimation issue can be addressed at least partially. Nevertheless, the development of jurisdiction-specific SPFs considering extended datasets and other facilities types (intersections, ramp segments, urban highways, rural two-lane highways, etc) is essential for improving the crash predictions.

5. Conclusions

Safety performance functions (SPFs) are essentially the key to the Highway Safety Manual prediction methodology used to estimate crash frequencies and crash hotspots identification. SPFs regression models are developed based on crash data from some selected states in the US. When applied to different jurisdictions, HSM recommends agencies to either develop local SPFs or calibrate HSM base SPFs to local conditions to enhance the accuracy of crash prediction, allowing them to make decisions pertaining to highway safety. This study aimed to calibrate HSM base-SPFs using crash data (2017-2019) for two multi-lanes rural highway segments (NHWY-80 and NHWY-85) KSA. Traffic and geometric data were primarily obtained from the ministry of transport (MOT) and partly from satellite images and field surveys. HSM calibration procedure was followed to estimate the local calibration factors. IHSDM calibrator tool was used for estimating the calibration factors. SPFs calibration results showed that HSM consistently overpredicts all types (total, FI, and PDO) of crashes. For NHWY-80, the estimated calibration factors were 0.71, 0.63, and 0.78 for Total, FI, and PDO crashes, respectively. Similarly, the computed calibration factors for NHWY-85 were 0.65, 0.53, and 0.78 for Total, FI, and PDO crashes, respectively. Quality assessment of the calibration efforts examined using different performance metrics such as MAD, MSPE and MPB showed the adequacy of the calibration process.

The outcome of this study may be used by local authorities for effective safety evaluation and guidance regarding the deployment of appropriate countermeasures to enhance road safety. Future studies could focus on other facilities such as urban highways, two-lane, two-way highways, ramps segments, speed lane changes, and intersections may be considered. It is suggested that forthcoming studies may utilize the disaggregate calibration factors for improving the precision of crash predictions. Other quality assessment techniques such as Cure plots, chi-square, and coefficient of variation (CV) may be used to assess the adequacy of the calibration process. Future studies could also focus on developing jurisdiction-specific SPFs for local conditions and compare them with calibrated SPFs. Finally, the transferability of HSM SPFs for other regions in KSA may be examined.

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