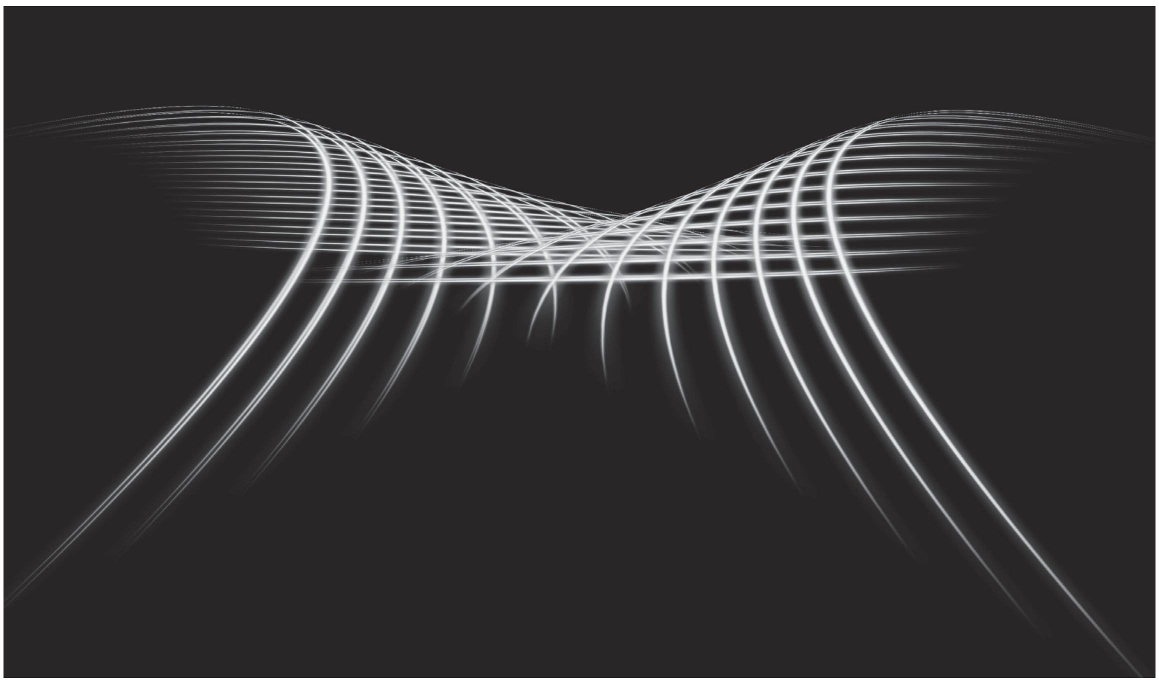
HCM2010

HIGHWAY CAPACITY MANUAL



VOLUME 4: APPLICATIONS GUIDE

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CHAPTER 37
TRAVEL TIME RELIABILITY: SUPPLEMENTAL

CONTENTS

LIST OF EXHIBITS

1. RELIABILITY VALUES FOR SELECTED U.S. FACILITIES

DATA SOURCES

Reliability data for 1 year of nonholiday weekday travel time were obtained from the following sources:

- 2-min traffic speed data in the I-95 corridor for 2010 (*1*), and
- 5-min traffic speed data in California for 2010 (*2*).

The first dataset includes freeway and urban street reliability data for states and metropolitan areas in the I-95 corridor (i.e., U.S. East Coast). The average speed of traffic was measured every 2 min for each Traffic Message Channel (TMC) road segment (*3*). Road segments vary but generally terminate at a decision point for the driver (e.g., intersection, start of left-turn pocket, ramp merge or diverge). Traffic speeds are obtained by monitoring the positions of GPS units in participating vehicles. A "free-flow reference speed" is also established for each TMC segment, but the method used to establish the reference speed is not disclosed.

The California data include freeway reliability data for the state's major metropolitan areas and reliability data for one urban street in Chula Vista. The data come from two sources: toll tag readers and loop detectors. California's system provides a function for stringing together a series of loop detector station speeds into an estimate of the overall average speed for the facility. The loop detector data used to compute an average speed for each segment of the facility are offset by the time taken by the average vehicle to traverse the upstream segment. Thus for a selected direction of travel, the average speed of vehicles in Segment 1 is used to compute the average travel time t for the selected time period (e.g., 5 min) for that segment starting at time $T = 0$. The mean speed is computed for the next downstream segment for the 5-min time period starting at $T = 0 + t$. The resulting mean travel times are then added together to get the average travel time of vehicles starting their trip at $0 < T < 5$ min.

RELIABILITY STATISTICS FOR A CROSS SECTION OF U.S. FACILITIES

Exhibit 37-1 through Exhibit 37-4 show the distribution of 50th percentile travel time index (TTI_{50}), mean travel time index (TTI_{mean}), and planning time index (PTI) observed in the dataset of U.S. freeways and urban streets described above for all time periods combined, the 2-h a.m. peak period, the 2-h midday period, and the 2-h p.m. peak period, respectively. These exhibits are expanded versions of Exhibit 36-6. They provide values in 5 percentile increments and include a combined set of values.

Exhibit 37-5 through Exhibit 37-7 present the source freeway data for the a.m. peak, midday, and p.m. peak periods, respectively. Exhibit 37-8 through Exhibit 37-10 present the source urban street data for the a.m. peak, midday, and p.m. peak periods, respectively.

Exhibit 37-1
Rankings of U.S. Facilities by Mean TTI and PTI (A.M. Peak, Midday, and P.M. Peak Combined)

	Freeways			Urban Streets		
Percentile Rank	**TTI_{50}**	**TTI_{mean}**	**PTI**	**TTI_{50}**	**TTI_{mean}**	**PTI**
Minimum	1.01	1.02	1.07	1.03	1.06	1.23
Worst 95%	1.02	1.05	1.09	1.09	1.12	1.27
Worst 90%	1.02	1.06	1.13	1.13	1.15	1.29
Worst 85%	1.04	1.06	1.14	1.15	1.16	1.32
Worst 80%	1.05	1.08	1.17	1.17	1.20	1.33
Worst 75%	1.05	1.08	1.22	1.19	1.20	1.35
Worst 70%	1.05	1.09	1.25	1.19	1.22	1.36
Worst 65%	1.06	1.10	1.30	1.20	1.22	1.39
Worst 60%	1.07	1.12	1.34	1.20	1.23	1.41
Worst 55%	1.08	1.15	1.39	1.21	1.23	1.42
Worst 50%	1.10	1.16	1.47	1.23	1.26	1.44
Worst 45%	1.11	1.19	1.57	1.24	1.27	1.47
Worst 40%	1.13	1.23	1.73	1.25	1.28	1.49
Worst 35%	1.14	1.30	1.84	1.25	1.29	1.52
Worst 30%	1.17	1.33	1.97	1.26	1.30	1.54
Worst 25%	1.20	1.39	2.24	1.30	1.34	1.60
Worst 20%	1.26	1.43	2.71	1.33	1.36	1.63
Worst 15%	1.31	1.51	2.90	1.35	1.38	1.70
Worst 10%	1.59	1.78	3.34	1.39	1.47	1.84
Worst 5%	1.75	1.97	3.60	1.45	1.54	1.98
Maximum	2.55	2.73	4.73	1.60	1.66	2.55

Source: Derived from directional values in Exhibit 37-5 through Exhibit 37-10. Entries are the lowest value for a category.

Notes: TTI_{50} = 50th percentile travel time index (50th percentile travel time divided by base travel time).
TTI_{mean} = mean travel time index (mean travel time divided by base travel time).
PTI = planning time index (95th percentile travel time divided by base travel time).
For freeways, the base travel time is the free-flow travel time. For urban streets, the base travel time corresponds to the 85th percentile highest speed observed during off-peak hours.

Exhibit 37-2
Rankings of U.S. Facilities by Mean TTI and PTI (A.M. Peak)

	Freeways			Urban Streets		
Percentile Rank	**TTI_{50}**	**TTI_{mean}**	**PTI**	**TTI_{50}**	**TTI_{mean}**	**PTI**
Minimum	1.01	1.02	1.07	1.03	1.06	1.24
Worst 95%	1.01	1.03	1.08	1.08	1.12	1.24
Worst 90%	1.03	1.05	1.12	1.12	1.13	1.27
Worst 85%	1.04	1.06	1.14	1.13	1.15	1.29
Worst 80%	1.04	1.08	1.14	1.14	1.16	1.29
Worst 75%	1.05	1.08	1.17	1.15	1.16	1.31
Worst 70%	1.06	1.09	1.24	1.16	1.17	1.33
Worst 65%	1.07	1.10	1.36	1.18	1.20	1.35
Worst 60%	1.08	1.11	1.40	1.19	1.20	1.37
Worst 55%	1.08	1.16	1.47	1.19	1.21	1.39
Worst 50%	1.09	1.17	1.53	1.20	1.23	1.41
Worst 45%	1.11	1.19	1.58	1.20	1.24	1.42
Worst 40%	1.12	1.21	1.70	1.22	1.26	1.44
Worst 35%	1.13	1.21	1.78	1.24	1.27	1.50
Worst 30%	1.15	1.25	1.89	1.24	1.28	1.52
Worst 25%	1.20	1.42	2.13	1.25	1.29	1.54
Worst 20%	1.28	1.48	2.61	1.26	1.29	1.57
Worst 15%	1.54	1.83	3.17	1.26	1.29	1.66
Worst 10%	1.72	1.93	3.55	1.28	1.31	1.71
Worst 5%	1.95	2.08	3.92	1.35	1.36	1.84
Maximum	2.17	2.73	4.66	1.38	1.49	2.13

Source: Derived from directional values in Exhibit 37-5 through Exhibit 37-10. Entries are the lowest value for a category.

Notes: TTI_{50} = 50th percentile travel time index (50th percentile travel time divided by base travel time).
TTI_{mean} = mean travel time index (mean travel time divided by base travel time).
PTI = planning time index (95th percentile travel time divided by base travel time).
For freeways, the base travel time is the free-flow travel time. For urban streets, the base travel time corresponds to the 85th percentile highest speed observed during off-peak hours.

Exhibit 37-3
Rankings of U.S. Facilities by Mean TTI and PTI (Midday)

	Freeways			Urban Streets		
Percentile Rank	**TTI_{50}**	**TTI_{mean}**	**PTI**	**TTI_{50}**	**TTI_{mean}**	**PTI**
Minimum	1.02	1.03	1.07	1.05	1.07	1.23
Worst 95%	1.02	1.04	1.08	1.08	1.10	1.27
Worst 90%	1.02	1.05	1.11	1.15	1.18	1.28
Worst 85%	1.02	1.06	1.14	1.16	1.18	1.30
Worst 80%	1.03	1.06	1.15	1.18	1.20	1.33
Worst 75%	1.04	1.08	1.17	1.19	1.21	1.34
Worst 70%	1.05	1.08	1.20	1.19	1.22	1.37
Worst 65%	1.05	1.09	1.21	1.20	1.22	1.39
Worst 60%	1.05	1.09	1.24	1.20	1.23	1.41
Worst 55%	1.06	1.11	1.26	1.21	1.23	1.42
Worst 50%	1.06	1.12	1.32	1.22	1.24	1.45
Worst 45%	1.07	1.13	1.34	1.24	1.27	1.47
Worst 40%	1.09	1.15	1.37	1.25	1.29	1.48
Worst 35%	1.09	1.15	1.43	1.25	1.30	1.51
Worst 30%	1.10	1.17	1.51	1.27	1.32	1.53
Worst 25%	1.12	1.26	1.65	1.30	1.34	1.57
Worst 20%	1.14	1.30	1.92	1.31	1.34	1.60
Worst 15%	1.16	1.32	2.41	1.32	1.35	1.63
Worst 10%	1.17	1.42	2.85	1.33	1.38	1.63
Worst 5%	1.21	1.46	3.16	1.35	1.42	1.86
Maximum	1.31	1.76	3.96	1.47	1.55	2.01

Source: Derived from directional values in Exhibit 37-5 through Exhibit 37-10. Entries are the lowest value for a category.

Notes: TTI_{50} = 50th percentile travel time index (50th percentile travel time divided by base travel time).
TTI_{mean} = mean travel time index (mean travel time divided by base travel time).
PTI = planning time index (95th percentile travel time divided by base travel time).
For freeways, the base travel time is the free-flow travel time. For urban streets, the base travel time corresponds to the 85th percentile highest speed observed during off-peak hours.

Exhibit 37-4
Rankings of U.S. Facilities by Mean TTI and PTI (P.M. Peak)

	Freeways			Urban Streets		
Percentile Rank	**TTI_{50}**	**TTI_{mean}**	**PTI**	**TTI_{50}**	**TTI_{mean}**	**PTI**
Minimum	1.01	1.05	1.10	1.13	1.14	1.32
Worst 95%	1.03	1.06	1.14	1.13	1.15	1.35
Worst 90%	1.04	1.06	1.22	1.18	1.21	1.35
Worst 85%	1.05	1.08	1.24	1.20	1.22	1.36
Worst 80%	1.05	1.09	1.28	1.20	1.22	1.37
Worst 75%	1.06	1.10	1.31	1.21	1.23	1.40
Worst 70%	1.07	1.14	1.32	1.22	1.23	1.41
Worst 65%	1.11	1.16	1.38	1.23	1.25	1.42
Worst 60%	1.14	1.23	1.59	1.24	1.26	1.44
Worst 55%	1.14	1.30	1.72	1.24	1.27	1.47
Worst 50%	1.17	1.31	1.85	1.25	1.28	1.49
Worst 45%	1.20	1.34	1.94	1.25	1.29	1.50
Worst 40%	1.21	1.36	2.06	1.31	1.33	1.52
Worst 35%	1.23	1.38	2.25	1.34	1.36	1.59
Worst 30%	1.26	1.41	2.46	1.35	1.38	1.64
Worst 25%	1.29	1.48	2.62	1.39	1.44	1.68
Worst 20%	1.35	1.57	2.77	1.41	1.49	1.78
Worst 15%	1.61	1.71	2.93	1.41	1.52	1.83
Worst 10%	1.70	1.86	3.26	1.49	1.56	1.88
Worst 5%	1.76	1.99	3.54	1.56	1.60	2.10
Maximum	2.55	2.73	4.73	1.60	1.66	2.55

Source: Derived from directional values in Exhibit 37-5 through Exhibit 37-10. Entries are the lowest value for a category.

Notes: TTI_{50} = 50th percentile travel time index (50th percentile travel time divided by base travel time).
TTI_{mean} = mean travel time index (mean travel time divided by base travel time).
PTI = planning time index (95th percentile travel time divided by base travel time).
For freeways, the base travel time is the free-flow travel time. For urban streets, the base travel time corresponds to the 85th percentile highest speed observed during off-peak hours.

Exhibit 37-5
Freeway Reliability Values: Weekday A.M. Peak Period

Location	Freeway	Length (mi)	FFS (mi/h)	Direction	Avg. Travel Time (min)	TTI_{mean}	PTI
Delaware	I-495	11.5	65	NB	11.0	1.03	1.08
Delaware	I-495	11.6	65	SB	11.1	1.03	1.07
Delaware	I-95	13.4	60	NB	14.6	1.10	1.37
Delaware	I-95	13.1	61	SB	13.5	1.05	1.13
Los Angeles	I-10	4.6	64	EB	4.5	1.06	1.12
Los Angeles	I-10	4.6	65	WB	4.5	1.08	1.14
Los Angeles	I-210	4.6	66	EB	4.9	1.17	1.57
Los Angeles	I-210	4.6	69	WB	4.6	1.16	1.57
Maryland	I-495 ES	26.5	63	SB	28.0	1.10	1.42
Maryland	I-495 ES	26.7	62	NB	31.1	1.20	1.71
Maryland	I-495 WS	15.4	60	NB	18.3	1.19	1.68
Maryland	I-495 WS	15.3	61	SB	26.9	1.78	2.71
Pennsylvania	I-76	3.7	51	EB	4.7	1.08	1.22
Pennsylvania	I-76	3.6	49	WB	6.5	1.49	3.06
Philadelphia	I-76	3.7	51	EB	4.7	1.08	1.22
Philadelphia	I-76	3.6	49	WB	6.5	1.79	3.06
Sacramento	US-50	6.0	69	EB	5.7	1.10	1.27
Sacramento	US-50	6.0	71	WB	6.2	1.21	1.78
Sacramento	I-80	12.4	68	EB	11.5	1.06	1.14
Sacramento	I-80	12.4	67	WB	12.0	1.09	1.17
San Diego	I-5	10.6	71	NB	11.1	1.23	1.81
San Diego	I-5	10.6	72	SB	9.1	1.02	1.07
San Diego	I-15	3.9	70	NB	4.7	1.41	2.10
San Diego	I-15	3.9	69	SB	7.3	1.58	3.38
San Francisco	I-880	4.6	71	NB	4.6	1.17	1.47
San Francisco	I-880	4.8	67	SB	8.2	1.92	3.57
San Francisco	I-680	4.2	66	NB	4.8	1.26	1.92
San Francisco	I-680	4.7	65	SB	5.2	1.21	1.49

Notes: FFS = free-flow speed.
TTI_{mean} = mean travel time index (mean travel time divided by free-flow travel time).
PTI = planning time index (95th percentile travel time divided by free-flow travel time).
NB = northbound, SB = southbound, EB = eastbound, WB = westbound, ES = east side, WS = west side.

Exhibit 37-6
Freeway Reliability Values: Weekday Midday Periods

Location	Roadway	Length (mi)	FFS (mi/h)	Direction	Avg. Travel Time (min)	TTI_{mean}	PTI
Delaware	I-495	11.5	65	NB	11.0	1.03	1.07
Delaware	I-495	11.6	65	SB	11.3	1.05	1.11
Delaware	I-95	13.4	60	NB	13.9	1.05	1.20
Delaware	I-95	13.1	61	SB	13.8	1.08	1.34
Los Angeles	I-10	4.6	64	EB	4.5	1.06	1.15
Los Angeles	I-10	4.6	65	WB	4.5	1.08	1.14
Los Angeles	I-210	4.6	66	EB	4.8	1.16	1.32
Los Angeles	I-210	4.6	69	WB	4.4	1.10	1.18
Maryland	I-495 ES	26.5	63	SB	27.2	1.07	1.31
Maryland	I-495 ES	26.7	62	NB	28.2	1.09	1.42
Maryland	I-495 WS	15.4	60	NB	20.5	1.34	2.69
Maryland	I-495 WS	15.3	61	SB	19.8	1.30	2.26
Pennsylvania	I-76	3.7	51	EB	5.0	1.13	1.39
Pennsylvania	I-76	3.6	49	WB	6.2	1.43	2.95
Philadelphia	I-76	3.7	51	EB	5.0	1.13	1.39
Philadelphia	I-76	3.6	49	WB	6.2	1.72	2.95
Sacramento	US-50	6.0	69	EB	5.8	1.11	1.20
Sacramento	US-50	6.0	71	WB	5.9	1.15	1.47
Sacramento	I-80	12.4	68	EB	11.8	1.09	1.25
Sacramento	I-80	12.4	67	WB	11.9	1.08	1.14
San Diego	I-5	10.6	71	NB	9.3	1.03	1.07
San Diego	I-5	10.6	72	SB	9.5	1.06	1.21
San Diego	I-15	3.9	70	NB	3.8	1.13	1.23
San Diego	I-15	3.9	69	SB	4.1	1.24	1.61
San Francisco	I-880	4.6	71	NB	4.5	1.17	1.53
San Francisco	I-880	4.8	67	SB	5.6	1.31	1.96
San Francisco	I-680	4.2	66	NB	4.4	1.15	1.34
San Francisco	I-680	4.7	65	SB	5.0	1.15	1.26

Notes: FFS = free-flow speed.
TTI_{mean} = mean travel time index (mean travel time divided by free-flow travel time).
PTI = planning time index (95th percentile travel time divided by free-flow travel time).
NB = northbound, SB = southbound, EB = eastbound, WB = westbound, ES = east side, WS = west side.

Exhibit 37-7
Freeway Reliability Values: Weekday P.M. Peak Period

Location	Roadway	Length (mi)	FFS (mi/h)	Direction	Avg. Travel Time (min)	TTI_{mean}	PTI
Delaware	I-495	11.5	65	NB	11.4	1.06	1.23
Delaware	I-495	11.6	65	SB	12.0	1.10	1.39
Delaware	I-95	13.4	60	NB	14.6	1.10	1.29
Delaware	I-95	13.1	61	SB	16.8	1.30	1.83
Los Angeles	I-10	4.6	64	EB	5.1	1.20	1.31
Los Angeles	I-10	4.6	65	WB	4.9	1.16	1.28
Los Angeles	I-210	4.6	66	EB	4.5	1.08	1.35
Los Angeles	I-210	4.6	69	WB	4.2	1.06	1.15
Maryland	I-495 ES	26.5	63	SB	33.3	1.31	1.85
Maryland	I-495 ES	26.7	62	NB	33.7	1.31	1.98
Maryland	I-495 WS	15.4	60	NB	41.8	2.73	4.73
Maryland	I-495 WS	15.3	61	SB	30.6	2.02	3.67
Pennsylvania	I-76	3.7	51	EB	6.0	1.36	1.94
Pennsylvania	I-76	3.6	49	WB	7.7	1.78	3.29
Philadelphia	I-76	3.7	51	EB	6.0	1.36	1.94
Philadelphia	I-76	3.6	49	WB	7.7	1.78	3.29
Sacramento	US-50	6.0	69	EB	7.0	1.35	2.12
Sacramento	US-50	6.0	71	WB	7.7	1.51	2.74
Sacramento	I-80	12.4	68	EB	13.9	1.28	1.84
Sacramento	I-80	12.4	67	WB	12.1	1.09	1.31
San Diego	I-5	10.6	71	NB	9.4	1.05	1.22
San Diego	I-5	10.6	72	SB	13.1	1.47	2.45
San Diego	I-15	3.9	70	NB	4.7	1.18	2.97
San Diego	I-15	3.9	69	SB	3.8	1.14	1.50
San Francisco	I-880	4.6	71	NB	7.7	1.96	3.43
San Francisco	I-880	4.8	67	SB	5.8	1.34	1.73
San Francisco	I-680	4.2	66	NB	6.1	1.59	2.74
San Francisco	I-680	4.7	65	SB	5.0	1.15	1.25

Notes: FFS = free-flow speed.
TTI_{mean} = mean travel time index (mean travel time divided by free-flow travel time).
PTI = planning time index (95th percentile travel time divided by free-flow travel time).
NB = northbound, SB = southbound, EB = eastbound, WB = westbound, ES = east side, WS = west side.

Exhibit 37-8
Urban Street Reliability Values: Weekday A.M. Peak Period

Location	Roadway	Length (mi)	FFS (mi/h)	Direction	Avg. Travel Time (min)	TTI_{mean}	PTI
California	Telegraph Canyon Rd.	4.4	45	EB	6.19	1.06	1.24
California	Telegraph Canyon Rd.	4.4	45	WB	6.57	1.12	1.42
Delaware	US-202	3.8	42	NB	6.97	1.28	1.55
Delaware	US-202	3.9	44	SB	6.52	1.20	1.41
Maryland	Hwy 175	7.4	38	NB	13.92	1.20	1.32
Maryland	Hwy 175	7.4	38	SB	14.00	1.21	1.35
Maryland	Hwy 193	5.9	33	EB	13.75	1.26	1.45
Maryland	Hwy 193	5.9	33	WB	13.72	1.27	1.52
Maryland	Hwy 198	10.1	42	EB	16.51	1.13	1.24
Maryland	Hwy 198	10.2	41	WB	16.95	1.15	1.27
Maryland	Hwy 355	4.2	30	NB	10.37	1.23	1.38
Maryland	Hwy 355	4.2	30	SB	12.57	1.49	2.13
Maryland	Randolph Rd.	6.7	35	EB	14.13	1.22	1.36
Maryland	Randolph Rd.	6.7	35	WB	15.28	1.31	1.71
Maryland	US-40	4.1	41	EB	7.00	1.16	1.29
Maryland	US-40	4.2	39	WB	8.50	1.29	1.85
Pennsylvania	US-1	8.0	33	NB	19.68	1.36	1.67
Pennsylvania	US-1	7.6	32	SB	18.18	1.29	1.52
Philadelphia	Hwy 611	3.4	20	NB	13.26	1.29	1.58
Philadelphia	Hwy 611	3.3	19	SB	12.89	1.25	1.41
South Carolina	US-378	5.5	44	EB	8.61	1.16	1.29
South Carolina	US-378	5.4	45	WB	8.37	1.16	1.31

Notes: FFS = free-flow speed.
TTI_{mean} = mean travel time index (mean travel time divided by base travel time).
PTI = planning time index (95th percentile travel time divided by base travel time).
NB = northbound, SB = southbound, EB = eastbound, WB = westbound.
The base travel time corresponds to the 85th percentile highest speed observed during off-peak hours.

Exhibit 37-9
Urban Street Reliability Values: Weekday Midday Periods

Location	Roadway	Length (mi)	FFS (mi/h)	Direction	Avg. Travel Time (min)	TTI_{mean}	PTI
California	Telegraph Canyon Rd.	4.4	45	EB	6.27	1.07	1.23
California	Telegraph Canyon Rd.	4.4	45	WB	6.46	1.10	1.28
Delaware	US-202	3.8	42	NB	7.28	1.34	1.63
Delaware	US-202	3.9	44	SB	6.93	1.28	1.47
Maryland	Hwy 175	7.4	38	NB	13.93	1.20	1.33
Maryland	Hwy 175	7.4	38	SB	14.17	1.23	1.38
Maryland	Hwy 193	5.9	33	EB	14.29	1.31	1.52
Maryland	Hwy 193	5.9	33	WB	13.99	1.29	1.49
Maryland	Hwy 198	10.1	42	EB	17.13	1.18	1.29
Maryland	Hwy 198	10.2	41	WB	17.47	1.18	1.27
Maryland	Hwy 355	4.2	30	NB	12.02	1.42	1.87
Maryland	Hwy 355	4.2	30	SB	13.07	1.55	2.01
Maryland	Randolph Rd.	6.7	35	EB	14.22	1.23	1.36
Maryland	Randolph Rd.	6.7	35	WB	14.62	1.25	1.42
Maryland	US-40	4.1	41	EB	7.44	1.23	1.47
Maryland	US-40	4.2	39	WB	8.01	1.22	1.42
Pennsylvania	US-1	8.0	33	NB	19.23	1.33	1.53
Pennsylvania	US-1	7.6	32	SB	19.02	1.35	1.58
Philadelphia	Hwy 611	3.4	20	NB	14.12	1.38	1.61
Philadelphia	Hwy 611	3.3	19	SB	13.78	1.34	1.63
South Carolina	US-378	5.5	44	EB	8.88	1.20	1.33
South Carolina	US-378	5.4	45	WB	8.78	1.22	1.40

Notes: FFS = free-flow speed.
TTI_{mean} = mean travel time index (mean travel time divided by base travel time).
PTI = planning time index (95th percentile travel time divided by base travel time).
NB = northbound, SB = southbound, EB = eastbound, WB = westbound.
The base travel time corresponds to the 85th percentile highest speed observed during off-peak hours.

Exhibit 37-10
Urban Street Reliability Values: Weekday P.M. Peak Period

Location	Roadway	Length (mi)	FFS (mi/h)	Direction	Avg. Travel Time (min)	TTI_{mean}	PTI
California	Telegraph Canyon Rd.	4.4	45	EB	6.71	1.14	1.35
California	Telegraph Canyon Rd.	4.4	45	WB	6.73	1.15	1.35
Delaware	US-202	3.8	42	NB	7.42	1.36	1.62
Delaware	US-202	3.9	44	SB	6.84	1.26	1.43
Maryland	Hwy 175	7.4	38	NB	14.20	1.23	1.36
Maryland	Hwy 175	7.4	38	SB	14.81	1.28	1.49
Maryland	Hwy 193	5.9	33	EB	16.39	1.50	1.83
Maryland	Hwy 193	5.9	33	WB	15.67	1.45	1.69
Maryland	Hwy 198	10.1	42	EB	18.53	1.27	1.50
Maryland	Hwy 198	10.2	41	WB	17.81	1.21	1.32
Maryland	Hwy 355	4.2	30	NB	14.03	1.66	2.11
Maryland	Hwy 355	4.2	30	SB	13.47	1.60	1.89
Maryland	Randolph Rd.	6.7	35	EB	16.11	1.39	1.65
Maryland	Randolph Rd.	6.7	35	WB	14.33	1.23	1.36
Maryland	US-40	4.1	41	EB	9.40	1.56	2.55
Maryland	US-40	4.2	39	WB	8.04	1.22	1.41
Pennsylvania	US-1	8.0	33	NB	19.63	1.36	1.53
Pennsylvania	US-1	7.6	32	SB	21.31	1.52	1.80
Philadelphia	Hwy 611	3.4	20	NB	13.22	1.29	1.48
Philadelphia	Hwy 611	3.3	19	SB	13.19	1.28	1.46
South Carolina	US-378	5.5	44	EB	9.22	1.24	1.41
South Carolina	US-378	5.4	45	WB	8.81	1.22	1.39

Notes: FFS = free-flow speed.
TTI_{mean} = mean travel time index (mean travel time divided by base travel time).
PTI = planning time index (95th percentile travel time divided by base travel time).
NB = northbound, SB = southbound, EB = eastbound, WB = westbound.
The base travel time corresponds to the 85th percentile highest speed observed during off-peak hours.

RELIABILITY STATISTICS FOR FLORIDA FREEWAYS

Exhibit 37-11 presents reliability statistics for a cross section of Florida freeways (*4*). The data were gathered and reported for the p.m. peak period (4:30 to 6:00 p.m.) and are *not* aggregated over the length of the facility. The data consist of spot speeds that have been inverted into travel time rates (min/mi).

The reliability statistics for Florida are reported separately from the rest of the United States because Florida was testing a variety of definitions of free-flow speed in the research from which these data were obtained (*4*). Florida usually sets the target free-flow speed for its freeways at the posted speed limit plus 5 mi/h. However, a target speed of 10 mi/h less than the posted speed limit and a policy target speed of 40 mi/h were also being tested for reliability computation purposes. The following statistics are presented:

- Four different TTIs (50th, 80th, 90th, and 95th percentile TTIs), based on a free-flow speed definition of the posted speed plus 5 mi/h;
- Two policy indices, one based on the 50th percentile speed and a target speed of the posted speed minus 10 mi/h, the other based on the 50th percentile speed and a target speed of 40 mi/h;
- A buffer time index, based on the 95th percentile speed and the mean speed; and
- A misery index, based on the average of the highest 5% of travel times and a free-flow travel time defined as the posted speed plus 5 mi/h.

Exhibit 37-11
Florida Freeway Reliability Statistics

Location	TTI_{50}	TTI_{80}	TTI_{90}	95% TTI (PTI)	Policy Index Alt. 1	Policy Index Alt. 2	Buffer Time Index	Misery Index
I-95 NB at NW 19th St.	1.00	1.36	1.69	2.01	1.27	1.75	2.02	2.22
I-95 SB at NW 19th St.	1.08	1.19	1.58	2.01	1.27	1.75	1.86	2.48
I-95 NB, S of Atlantic Blvd.	1.03	1.28	1.73	2.23	1.27	1.75	2.16	2.74
I-95 SB, S of Atlantic Blvd.	1.10	1.36	1.89	2.37	1.27	1.75	2.15	2.93
SR 826 NB at NW 66th St.	2.40	2.82	3.07	3.35	1.33	1.50	1.39	3.69
SR 826 SB at NW 66th St.	1.01	1.28	2.63	4.06	1.33	1.50	4.02	4.62
SR 826 WB, W of NW 67th Ave.	1.04	1.08	1.21	1.77	1.33	1.50	1.70	2.10
SR 826 EB, W of NW 67th Ave.	0.98	1.00	1.02	1.04	1.33	1.50	1.07	1.10
I-4 EB, W of World Dr.	0.97	1.04	1.06	1.08	1.27	1.75	1.12	1.12
I-4 WB, W of World Dr.	1.02	1.09	1.49	1.90	1.27	1.75	1.86	2.22
I-4 EB, W of Central Florida Pkwy.	1.06	1.13	1.18	1.31	1.27	1.75	1.24	1.56
I-4 WB, W of Central Florida Pkwy.	1.05	1.36	1.63	1.81	1.27	1.75	1.72	2.03
I-275 NB, N of MLK Jr Blvd.	1.45	1.71	1.91	2.16	1.33	1.50	1.49	2.58
I-275 SB, N of MLK Jr Blvd.	0.97	1.01	1.04	1.12	1.33	1.50	1.15	1.28
I-275 NB, N of Fletcher Blvd.	1.05	1.07	1.11	1.21	1.33	1.50	1.16	1.35
I-275 SB, N of Fletcher Blvd.	0.96	0.98	0.99	1.00	1.33	1.50	1.04	1.01
I-10 EB, E of Lane Ave.	0.93	0.96	0.98	0.99	1.33	1.50	1.07	1.01
I-10 WB, E of Lane Ave.	0.97	1.10	1.24	1.46	1.33	1.50	1.51	1.87
I-95 NB, S of Spring Glen Rd.	1.04	1.09	1.26	1.77	1.27	1.75	1.70	2.00
I-95 SB, S of Spring Glen Rd.	1.16	1.30	1.42	1.60	1.27	1.75	1.38	1.88
Minimum	0.93	0.96	0.98	0.99	1.27	1.50	1.04	1.01
Average	1.11	1.26	1.51	1.81	1.30	1.63	1.64	2.09
Maximum	2.40	2.82	3.07	4.06	1.33	1.75	4.02	4.62

Source: Adapted from Kittelson & Associates, Inc. (*4*).

Notes: TTI_{xx} = travel time index based on the percentile speed indicated in the subscript and a free-flow speed defined as the posted speed plus 5 mi/h.
PTI = planning time index.
Policy Index Alternative 1 = index based on the 50th percentile speed and a target speed of the posted speed minus 10 mi/h.
Policy Index Alternative 2 = index based on the 50th percentile speed and a target speed of 40 mi/h.
Buffer time index = index based on the ratio of the 95th percentile and mean travel speeds.
Misery index = index based on the ratio of (*a*) the average of the highest 5% of travel times and (*b*) a free-flow travel time defined as the posted speed plus 5 mi/h.
N = north, S = south, E = east, W = west, NB = northbound, SB = southbound, EB = eastbound, WB = westbound.

2. ALTERNATIVE FREEWAY INCIDENT PREDICTION METHOD

As discussed in the Data Acquisition section of Chapter 36, Travel Time Reliability, freeway incident probabilities can be estimated directly only in the rare cases where incident logs are complete and accurate over the entire reliability reporting period. On the other hand, data on the number of crashes on a specific facility or a specific type of facility (e.g., all freeways in a region) are usually obtainable. This section presents a method for estimating facility incident probabilities from a known or predicted crash rate on the basis of the assumption that the number of incidents in a given study period is Poisson distributed (*5*, *6*).

Equation 37-1 estimates the expected number of incidents n_j during the study period under a given demand pattern j as a function of the facility's crash rate, the ratio of incidents to crashes, the traffic demand, and the facility length:

Equation 37-1

$$n_j = CR \times ICR \times (AADT \times 10^{-8} \times D \times \frac{DR_j}{DM} \times K_s) \times L_f$$

where

- n_j = expected number of incidents during the study period under demand pattern j,
- CR = local (facility or regional freeway) crash rate per 100 million vehicle miles traveled (VMT) (crashes/100 million VMT),
- ICR = local incident-to-crash ratio (unitless),
- $AADT$ = annual average daily traffic (veh),
- D = directional distribution of traffic demand (decimal),
- DR_j = demand ratio for demand pattern j (unitless),
- DM = demand multiplier (pattern independent) (unitless),
- K_s = proportion of daily demand volume that occurs during the study period (pattern independent), and
- L_f = facility length (mi).

The arrival of vehicles involved in an incident is assumed to follow the Poisson distribution. Thus, the probability $P_j(X)$ of X incidents in demand pattern j, with an expected number of incidents n_j during the study period under demand pattern j, is estimated from the following:

Equation 37-2

$$P_j(X) = \frac{n_j^X}{X!} e^{-n_j}$$

The probability of *no* incidents occurring in demand pattern j is then simply

Equation 37-3

$$P_j(0) = \frac{n_j^0}{0!} e^{-n_j} = e^{-n_j}$$

Finally, the probability of *at least one* incident occurring in demand pattern j is 1 minus the probability of no incidents occurring:

$$P_j(>0) = 1 - P(0) = 1 - e^{-n_j}$$

Equation 37-4

Estimating the probability of occurrence of a specific incident type i requires data on the fraction of all incidents that are of that type and their average duration. These items can be determined from local data, or in the absence of such data the national default values given in Chapter 36 can be applied. The overall duration of a given incident type i is computed by weighting the probability of incident type i by its expected duration; the linear correlation of the incident probability with traffic demand is recognized from Equation 37-1. Since the units for the number of incidents X are based on the study period, the incident duration must also be expressed in the same unit of study period (e.g., minutes or hours).

If g_i is the proportion of all incidents that are of type i, t_{SP} is the study period duration (minutes or hours), and t_E is the average incident event duration (minutes or hours), the time-based probability of at least one incident of type i in demand pattern j is the following:

$$P_{i,j} = 1 - e^{-(n_j g_i)(t_E/t_{SP})}$$

Equation 37-5

Repeating the compuation of Equation 37-5 for all combinations of incident types and demand patterns allows the development of the incident probability matrix that is required as an input to the freeway reliability method.

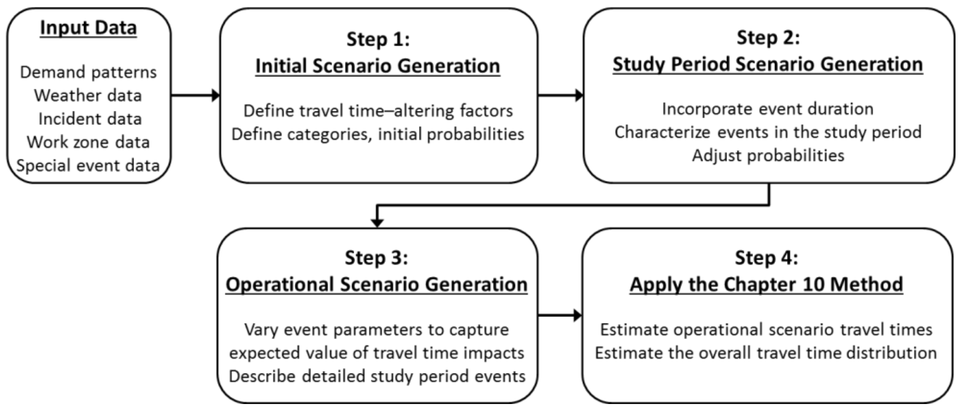
3. FREEWAY SCENARIO GENERATION

INTRODUCTION

This section provides details of the freeway scenario generation process. An overview of this process is provided in Chapter 36, Travel Time Reliability.

Freeway scenario generation is a deterministic process. This approach enumerates different operational conditions of a freeway facility on the basis of different combinations of factors affecting travel time. Each unique set of operational conditions forms a *scenario.* Four principal steps are involved in the scenario generation process, as shown in Exhibit 37-12.

Exhibit 37-12
Process Flow Overview for Freeway Scenario Generation



Scenario generation can work in both data-rich and data-poor environments, as well as anywhere in between. In a data-rich environment, the analyst uses local data as much as possible. In a data-poor setting, the analyst relies on national default values to generate the scenarios. At a minimum, the analyst must provide facility AADT, geographic location, and detailed geometric data, as in the case of a *Highway Capacity Manual* (HCM) operations analysis.

INITIAL SCENARIO GENERATION

The freeway scenario generator develops and assigns initial probabilities to a number of *initial scenarios,* combinations of events that occur within a given time period (such as a weekday or, more likely, a few hours thereof). An initial scenario's probability is expressed as the fraction of time a particular combination of events (e.g., demand, weather, incidents) takes place during the study period of interest.

Initial scenario probabilities are computed by assuming independence between events. During this stage of scenario generation, the probabilities do not take into account the actual duration of the event in question. They only account for the categories of weather or incidents. Therefore, the initial probabilities must be adjusted to account for actual event durations; in some cases, the event durations themselves must be adjusted. The rationale for making these adjustments is described in detail in the Motivation Using a Simple Example subsection.

Assumptions

The following assumptions are made in generating initial scenarios:

- The factors contributing to travel time variation are independent. The method provides the ability to vary some factors (e.g., demand by weather type), but not until later in the process, when operational scenarios are generated.
- Each factor that contributes to travel time variability is categorized into discrete categories with timewise probabilities of occurrence (not frequencies or chance of occurrence). If local probabilities are not available, alternative methodologies are used (e.g., application of default values) to estimate those probabilities.
- The time unit for scenario generation is minutes. Every calculation for measuring probability is based on minutes. However, any other time unit can be used and expressed as a fractional number.
- Any time instance in the study period or reliability reporting period is independent of other time instances.

Required Input Data

This subsection describes the data required for calculating an initial scenario's probabilities. In general, the timewise probabilities of all the various types of events contributing to travel time variation should be known. Incident and weather probabilities do not deal with the frequency or counts of those events. Instead, event frequencies are estimated from given timewise probabilities and expected durations of different types of events.

Demand Variability

Demand is categorized by defining demand patterns within the reliability reporting period. Days with similar demand levels are assigned to a single demand pattern. Demand patterns are defined in two dimensions, which account for month-of-year and day-of-week demand variability within the reliability reporting period. Monthly variability usually reflects seasonal demand effects, while day-of-week variability reflects the effect of daily variation in demand levels.

Demand ratios must be provided for each combination of weekday (up to 7 days) and month (up to 12 months) within the reliability reporting period (up to 84 total values). The demand ratios are expressed as the average daily traffic (ADT) for a given day–month combination relative to either (*a*) a specific day–month combination or (*b*) AADT. In addition, a *demand multiplier* must be provided, defined as the demand ratio for the base dataset's demand. If the base dataset's demands are reflective of AADT and the supplied demand ratios are relative to AADT, for example, the demand multiplier will be 1.00.

Once the demand ratios have been developed, the analyst can optionally define demand patterns based on combinations of days and months with similar demand ratios (e.g., Mondays, Tuesdays, and Wednesdays in summer months). The use of demand patterns reduces the number of scenarios that are ultimately generated, which directly affects the time required for performing a reliability analysis.

The probability of a given demand pattern d, $P_{DP}(d)$, is the portion of the reliability reporting period represented by the demand pattern (in minutes) divided by the total number of study period (SP) minutes in the reliability reporting period (RRP):

Equation 37-6

$$P_{DP}(d) = \frac{\text{sum of SP minutes within demand pattern } d}{\text{sum of SP minutes in RRP}}$$

For example, if a demand pattern consists of Thursdays in March, April, and May; the study period is defined as 6 h; and the reliability reporting period is defined as all weekdays in a year (261 days), then the probability of occurrence of this demand pattern is the following:

$$P_{DP} = \frac{(13 \text{ weeks})\times(1 \text{ day})\times(6 \text{ h/day})\times(60 \text{ min/h})}{(261 \text{ days})\times(6 \text{ h/day})\times(60 \text{ min/h})} = 4.98\%$$

Weather Variability

Chapter 10, Freeway Facilities, provides 15 categories of weather events that influence freeway capacity. Five of these categories have a negligible (<4%) effect on freeway capacity and are therefore not addressed further in the reliability methodology. The remaining 10 *severe weather* categories and a non–severe weather category are considered, as shown in Exhibit 36-4. The probability of each of these 11 weather events must be provided for each month within the reliability reporting period (up to 12 months), for a total of up to 132 values.

In data-rich environments where agencies have access to detailed local weather data, the probability $P_W(w, m)$ of weather type w in month m is computed on the basis of Equation 37-7. Weather types are mutually exclusive, so when two or more categories may be identified for the same time period (i.e., low visibility and heavy rain), the time is assigned to the category with the largest capacity effect.

Equation 37-7

$$P_W(w, m) = \frac{\text{sum of SP durations in month } m \text{ with weather type } w \text{ (min)}}{\text{sum of all SP durations in month } m \text{ (min)}}$$

The method provides the analyst with the option of removing weather events with very low probabilities to reduce the overall number of scenarios. Any weather event with a probability lower than the analyst-specified threshold is removed, and its probability is assigned to the remaining weather events in proportion to their probabilities. Use of a large value for this threshold is not recommended, since it can introduce bias and shift the resulting travel time distribution.

Incident Variability

Incidents are categorized on the basis of their capacity impacts. Six incident types are defined: no incident; shoulder closure only; and one-, two-, three-, and four-lane closures. The following is the probability $P_{INC}(i, m)$ of incident type i occurring in month m:

$$P_{INC}(i,m) = \frac{\text{sum of SP durations in month } m \text{ with incident type } i \text{ (min)}}{\text{sum of all SP durations in month } m \text{ (min)}}$$

Equation 37-8

If local incident probabilities are not available for a facility, local crash rates or crash rates predicted from the Highway Economic Requirements System model (7) can be used along with an incident-to-crash ratio to calculate the probabilities of incident types. This process was described in Section 2, Alternative Freeway Incident Prediction Method.

Independence of Time Instances and Joint Events

The event probabilities provided as input data reflect the frequency of an event occurrence during a specified time period (e.g., heavy snow in January). However, the scenario generator computes *timewise probabilities* of an event—the chance of exposure to a specific event during any minute within a study period or the reliability reporting period. From a mathematical perspective, the durations of weather and incident events are not considered in the initial scenario generation step. Any minute within a study period or reliability reporting period is therefore assumed to be independent of any other minute. More precisely, the state of any event in any minute has no impact on the probability of any other event in any other minute.

One basic assumption is that all factors contributing to travel time variation are independent. Thus, the probability of an initial scenario is the product of the probabilities of all contributing factors. For example, there is no dependency between certain demand levels and different weather types. The freeway reliability method combines these categories and multiplies their probabilities to generate the different operational conditions of the freeway facility that are known as initial scenarios.

Equation 37-9 demonstrates the joint probability of a particular initial scenario on the basis of the probability of the scenario's weather and incident conditions, under the assumption of independence between factors.

$$P\{\text{demand pattern d, weather type w, incident type i}\} =$$
$$P\{\text{demand pattern } d\} \times P\{\text{weather type } w\} \times P\{\text{incident type } i\} =$$
$$P_{DP}(d) \times P_{w}^{DP}(d,w) \times P_{INC}^{DP}(d,i)$$

Equation 37-9

Some dependencies between different types of events are inherent through use of the calendar. For example, both demand levels and weather conditions are associated with the calendar; therefore, a correlational (not a causal) relationship exists between the two factors. Incident probabilities are also tied to prevailing demand levels, again providing a correlation through the calendar. The analyst can provide specific monthly crash or incident rates to the scenario generator to express further association between weather and incident probabilities.

Aggregation of Probabilities Across Demand Patterns

An initial scenario is characterized by its demand pattern, weather, and incident type. The scenario's probability can be computed from Equation 37-9. However, the probabilities of weather and incidents are provided as monthly values, while demand is categorized on the basis of a demand pattern definition that is often not monthly. Thus, the probabilities of weather and incidents must be aggregated across the various demand patterns. The demand pattern–dependent probabilities of weather $P_W^{DP}(w, m)$ for weather type w in month m and of incidents $P_{INC}^{DP}(i, m)$ of type i in month m for demand pattern d are computed from Equation 37-10 and Equation 37-11, respectively.

Equation 37-10

$$P_w^{DP}(d,w) = \frac{\sum_{\forall m \in DP} P_w(w,m) \times N_{DP}(d,m)}{\sum_{\forall m \in DP} N_{DP}(d,m)}$$

Equation 37-11

$$P_{INC}^{DP}(d,i) = \frac{\sum_{\forall m \in DP} P_{INC}(i,m) \times N_{DP}(d,m)}{\sum_{\forall m \in DP} N_{DP}(d,m)}$$

where $N_{DP}(d,m)$ is the number of days in demand pattern d occurring in month m in the RRP and other variables are as defined previously.

An initial scenario describes the operational condition of the freeway facility and the probability associated with it. This probability is the expected portion of time that the freeway facility is subject to operations under the conditions specified for the scenario. Thus, each initial scenario presents an expected travel time and its associated probability. By modeling these scenarios and measuring their travel times, a discrete distribution of expected travel times is generated, which can subsequently be used to assess the freeway facility's reliability.

STUDY PERIOD SCENARIO GENERATION

While the initial scenarios describe the general conditions under which a facility will operate (e.g., a weather event will occur sometime during the study period, an incident will take place sometime and somewhere on the facility), they lack the specificity that allows an event's effect on facility performance on a given day to be evaluated.

Study period scenarios specify event time durations and the corresponding adjustments to initial scenario probabilities. A unique study period is associated with each initial scenario. The only difference between an initial scenario and a study period scenario is the probability associated with each. This subsection describes the computations required to achieve this transition.

Motivation Using a Simple Example

Facility Description

Consider a freeway facility consisting of 10 HCM segments. The reliability reporting period contains 50 workday Fridays, each of which has the same demand pattern. The study period is 3 to 7 p.m., resulting in sixteen 15-min analysis periods.

For simplicity, one severe weather condition and one incident are considered in the reliability reporting period: medium rain with a total duration of 600 min in the reliability reporting period and one lane closure with a total duration of 900 min in the reliability reporting period. Exhibit 37-13 summarizes these conditions with respect to their timewise probabilities.

The timewise probability expresses the likelihood of an event occurring in any time instance during the reliability reporting period. This probability translates into any time period that one can report. For example, if the duration of the study period is 4 h, the event is expected to be present for a period of time equal to its probability times the study period duration. The term "timewise" distinguishes it from other types of probabilities, such as VMT-wise, countwise, or lengthwise probabilities.

Exhibit 37-13
Example Timewise Probabilities of Event Occurrences

Event	Timewise Probability of Occurrence
WEATHER EVENT	
Medium rain	$\frac{\text{600 min duration}}{\text{50 study periods} \times \text{4 h/study period} \times \text{60 min/h}} = 0.05$
Non–severe weather	$1 - 0.05 = 0.95$
INCIDENT EVENT	
One-lane closure	$\frac{\text{900 min duration}}{\text{50 study periods} \times \text{4 h/study period} \times \text{60 min/h}} = 0.075$
No incident	$1 - 0.075 = 0.925$

Initial Scenario Development

The initial scenario generation procedure is used to generate different operational conditions on the freeway facility. These conditions are assumed to be independent. Exhibit 37-14 summarizes the operational conditions associated with the initial scenarios in this example.

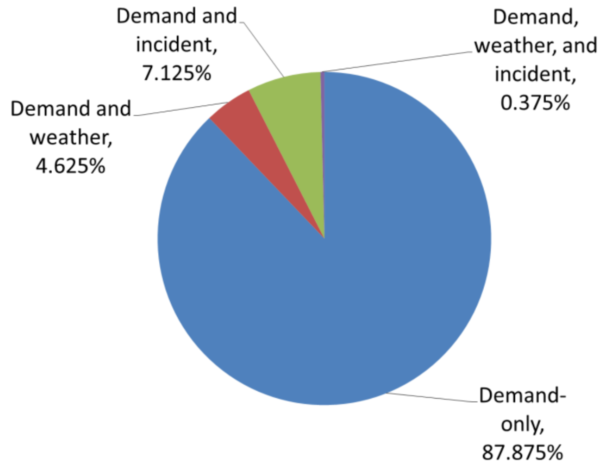
Exhibit 37-14
Example Initial Scenarios

Initial Scenario Number	Weather Condition	Incident Condition	Initial Scenario Description	Probability
1	Non–severe	No incident	Demand-only	$P_1 = 0.95 \times 0.925 = 0.87875$
2	Medium rain	No incident	Demand and weather	$P_2 = 0.05 \times 0.925 = 0.04625$
3	Non–severe	1 lane closed	Demand and incident	$P_3 = 0.95 \times 0.075 = 0.07125$
4	Medium rain	1 lane closed	Demand, weather, and incident	$P_4 = 0.05 \times 0.075 = 0.00375$
				Sum=1

The initial scenarios in the above form are not ready for use in the HCM Chapter 10 methodology, since they do not contain any of the critical event attributes that affect travel time (e.g., location, duration, start time).

The joint probabilities of these operational conditions are timewise as well. If any time instance across all study periods in the reliability reporting period is chosen, it will yield a non-severe-weather and no-incident condition (demand-only scenario) with a probability of almost 88%. Exhibit 37-15 depicts the probabilities associated with each initial scenario.

Exhibit 37-15
Distribution of Initial Scenario Categories



Study Period Scenario Development

Next, the event durations are introduced. On the basis of historical data, the average durations for the one-lane closure incident and the medium rain event are 49 and 32 min, respectively. Because the Chapter 10 freeway facilities method uses 15-min analysis periods, these average durations are rounded to 45 and 30 min, respectively (three and two analysis periods, respectively).

To accommodate the four combinations of weather and incident events being modeled, four study period scenarios are defined. Modeling these four study periods guarantees that all the operational condition characteristics are accounted for at the correct timewise probabilities. A weight (or probability), the *study period scenario probability,* is assigned to these study periods for full consistency with the specified likelihood of the operational conditions (initial scenarios).

The objective now is to determine what weight to give to each of the four study period scenarios so that the resulting travel time distribution represents the prespecified operational conditions of the facility. In other words, in view of the initial scenario probability values P_1, P_2, P_3, and P_4 and the respective durations of the events and the study period, what should be the study period scenario probability values π_1, π_2, π_3, and π_4 that would provide consistent time-based probabilities throughout? *The study period scenario probabilities should be selected in such a way that the likelihoods of the conditions modeled are identical to the initial scenario probabilities.*

To achieve this result, the equalities given below covering each of the initial scenarios must be satisfied. The logic behind each equation is to equalize the proportion of time each study period scenario should be represented on the basis of the initial scenario probabilities; it is recognized that there are periods of no-incident or non–severe weather conditions in all four study periods.

For example, in study period Scenario 2 (medium rain and no incident), severe weather occurs in two of the 16 analysis periods, meaning that no-incident and non–severe weather conditions are present in the remaining 14 analysis periods. Similarly, in study period Scenario 3 (non–severe weather and a one-lane-closure incident), the incident is present in three of the 16 analysis periods and no-event conditions are present in the remaining 13 analysis periods. Finally, in study period Scenario 4 (medium rain and a one-lane-closure incident), the longer of the two durations (in this case, three analysis periods) determines when any event is present, while the shorter of the two durations (in this case, two analysis periods) determines how long the combined weather and incident condition occurs.

Equation 37-12 provides the equality relationship for Initial Scenario 1, which represents a demand-only condition. The probability of this scenario must equal the combined probabilities of the demand-only portions of the four study period scenarios.

$$P_1 = \left(\frac{16-0}{16}\right)\pi_1 + \left(\frac{16-2}{16}\right)\pi_2 + \left(\frac{16-3}{16}\right)\pi_3 + \left(\frac{16-3}{16}\right)\pi_4$$

Equation 37-12

Study period Scenario 1 has 16 demand-only analysis periods out of 16 total analysis periods, study period Scenario 2 has 14 such analysis periods out of 16, and so on. The proportion of demand-only analysis periods in each study period scenario is multiplied by that scenario's probability π_i.

Equation 37-13 provides the equality relationship for Initial Scenario 2, which represents a combined demand and severe weather event condition. This condition does not occur at all in study period Scenarios 1, 3, or 4, and it only occurs during two of the 16 analysis periods during study period Scenario 2. This leads to the following result:

$$P_2 = \left(\frac{2}{16}\right)\pi_2$$

Equation 37-13

Similarly, a combined demand and incident condition occurs during three of the 16 analysis periods in study period Scenario 3 and in one of the 16 analysis periods in study period Scenario 4. A combined demand, weather, and incident condition occurs only during two of the 16 analysis periods in study period Scenario 4. Equation 37-14 and Equation 37-15 give the respective equality relationships for Initial Scenarios 3 and 4.

$$P_3 = \left(\frac{3}{16}\right)\pi_3 + \left(\frac{1}{16}\right)\pi_4$$

Equation 37-14

$$P_4 = \left(\frac{2}{16}\right)\pi_4$$

Equation 37-15

The above system of four equations in four unknowns can be solved for the various π_i values, with the following results:

$$\pi_1 = 0.23; \pi_2 = 0.37; \pi_3 = 0.37; \text{and } \pi_4 = 0.03.$$

If these π_i values are assigned to the four specified study period scenarios, the resulting travel time distribution will yield facility travel times consistent with the intended distribution of the operational conditions.

Note the large difference between P_1 (88%) and π_1 (23%). This does not mean that normal conditions have been reduced by this amount in the study period scenarios. It is simply reflective of the fact that "pieces" of P_1 exist in all four study period scenarios, as indicated in the first of the four equilibrium equations above. Similarly, the large disparity between P_2 and π_2 and between P_3 and π_3 is

The large difference in P_1 and π_1 values reflects the existence of pieces of the no-incident, non–severe weather initial scenario in all four study period scenarios.

explained by the fact that these two study period scenarios also contain many no-incident, non–severe weather analysis periods.

The set of equilibrium equations could yield infeasible results (meaning that one of the resulting π_i values is negative). This could occur if the likelihood of the weather or incident event is high and the expected event duration is short. In these cases, the duration of the event should be increased or more than one event per study period should be modeled.

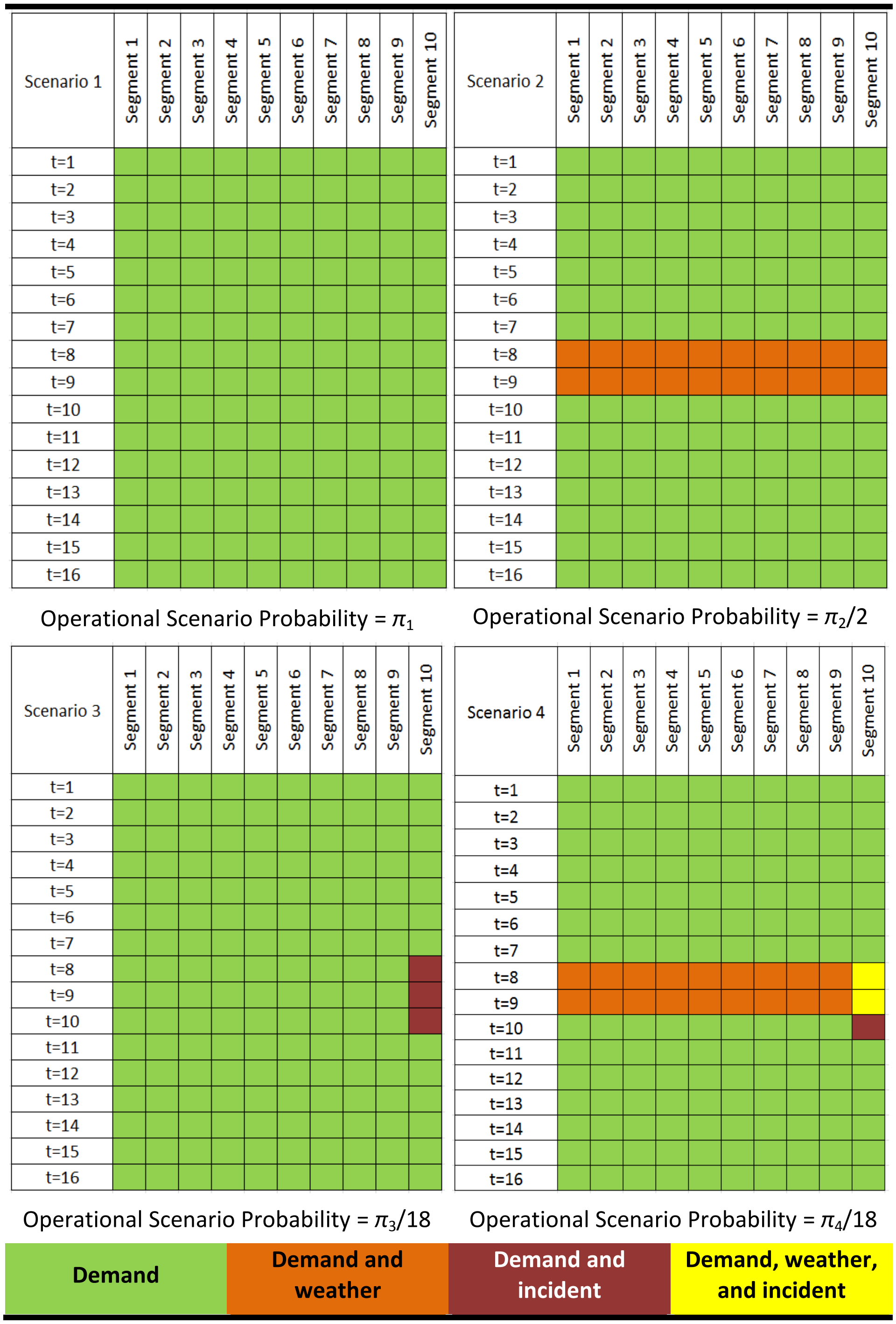
Operational Scenario Development

The final step in the scenario generation process is to develop the operational scenarios. There are two possible start times for weather events, along with three possible start times, three possible durations, and two possible locations for incidents. Each possible combination is assumed to occur with equal probability.

Exhibit 37-16 shows one possible operational scenario in each of the four study periods associated with a study period scenario. Each study period is 4 h (or 16 analysis periods) long, consistent with the specified duration. The exhibit shows the expected duration and location of the weather and incident events associated with the operational scenarios.

At this point, sufficient information is available to model the facility with the Chapter 10 freeway facilities method, since the weather and incident events have been fully specified in terms of their start time, duration, and affected segments. In addition, the probabilities of each operational scenario have been determined, allowing the resulting travel time distribution to be aggregated properly.

Exhibit 37-16
Events Occurring During Each Analysis Period of Selected Operational Scenarios



Algorithm Assumptions

The following assumptions are incorporated into the algorithm for developing study period scenario probabilities:

- The duration of incident events may be altered in the development of the operational scenarios later in the process without altering the study period probabilities. This assumption is not overly severe, since the three possible incident durations are selected to be at, below, and above the mean duration.
- All events are rounded to the nearest 15-min increment. This process potentially introduces some errors and bias to the reliability calculations; however, the method accounts for this bias and eliminates its effects.

Scenario Categories

Scenarios are divided into four categories:

1. Demand-only scenarios (normal condition),
2. Demand with weather scenarios,
3. Demand with incident scenarios, and
4. Demand with weather and incident scenarios.

This categorization is needed to execute the probability adjustment procedure when study period scenarios are generated. Typically, the demand-only category has a high probability of occurrence. Demand patterns are modeled by using the demand ratios. Each scenario (initial, study period, or operational) has an associated demand multiplier that applies to all segments and time periods.

To model the impacts of weather and incident events, appropriate capacity adjustment factors (CAFs) and free-flow speed adjustment factors (SAFs) are applied to the affected segments and time periods. For incidents, the number of open lanes is also adjusted on the basis of the type of incident.

Subsets of Initial Scenarios

In a facility with N demand patterns, all initial scenarios could be divided into N subsets. These subsets are mutually exclusive, and their union covers all initial scenarios. The methodology for adjusting the probabilities of study period scenarios applies to each subset separately.

Exhibit 37-17 presents an example of one such subset associated with one specific demand pattern that has a probability of occurrence of 14.18%.

Exhibit 37-17
Example Subset of Initial Scenarios Associated with a Demand Pattern

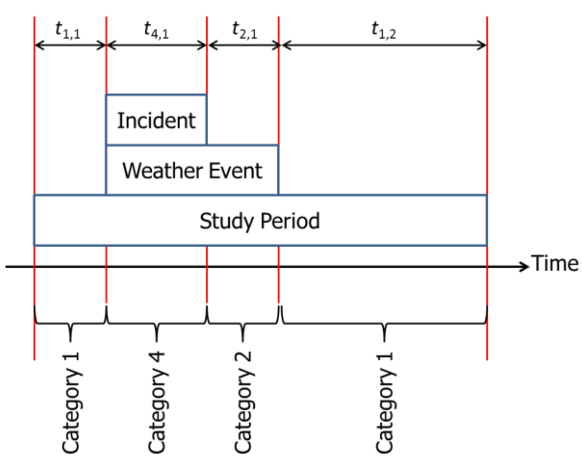
Initial Scenario No.	Demand Pattern	Weather Type	Incident Type	Initial Scenario Probability (%)	Scenario Category
4	1	Normal weather	No incident	8.84736	1
16	1	Normal weather	Shoulder closed	3.00484	3
28	1	Normal weather	1 lane closed	0.90935	3
29	1	Light snow	No incident	0.44710	2
42	1	Normal weather	2 lanes closed	0.23029	3
45	1	Normal weather	3 lanes closed	0.18409	3
48	1	Light snow	Shoulder closed	0.14825	4
49	1	Medium rain	No incident	0.14309	2
68	1	Low visibility	No incident	0.06633	2
74	1	Medium rain	Shoulder closed	0.05025	4
77	1	Light snow	1 lane closed	0.04479	4
88	1	Low visibility	Shoulder closed	0.02332	4
96	1	Light–medium snow	No incident	0.01666	2
99	1	Medium rain	1 lane closed	0.01524	4
104	1	Light snow	2 lanes closed	0.01134	4
117	1	Light snow	3 lanes closed	0.00906	4
120	1	Low visibility	1 lane closed	0.00707	4
128	1	Light–medium snow	Shoulder closed	0.00531	4
138	1	Medium rain	2 lanes closed	0.00386	4
146	1	Medium rain	3 lanes closed	0.00309	4
163	1	Low visibility	2 lanes closed	0.00179	4
164	1	Light–medium snow	1 lane closed	0.00160	4
166	1	Low visibility	3 lanes closed	0.00143	4
203	1	Light–medium snow	2 lanes closed	0.00040	4
209	1	Light–medium snow	3 lanes closed	0.00032	4

Conceptual Approach

The study period probability adjustment method creates weather or incident events in the study period with a predetermined duration. The remaining time periods in that study period actually describe another scenario (usually the normal condition, Scenario Category 1). Therefore, each study period scenario is in fact associated with more than one initial scenario.

Exhibit 37-18 shows an example where a study period scenario contains three initial scenario categories: demand-only (during $t_{1,1}$ and $t_{1,2}$), demand with weather (during $t_{2,1}$), and demand with weather and incident (during $t_{4,1}$).

Exhibit 37-18
Example Study Period with Incident and Weather Events



If the probability of occurrence of a study period is given as Π, then the probability of occurrence $P(s)$ of a particular scenario category s that appears i times within the study period with individual durations $t_{s,i}$ is as follows:

Equation 37-16

$$P(s) = \Pi \times \left(\frac{\sum_i t_{s,i}}{t_{SP}} \right)$$

where t_{SP} is the study period duration in minutes.

For the situation shown in Exhibit 37-18, the study period scenario probabilities are as follows:

$$P(1) = \Pi \times \left(\frac{t_{1,1} + t_{1,2}}{t_{SP}} \right)$$

$$P(2) = \Pi \times \left(\frac{t_{2,1}}{t_{SP}} \right)$$

$$P(3) = 0$$

$$P(4) = \Pi \times \left(\frac{t_{4,1}}{t_{SP}} \right)$$

As shown in the above equations, there is a one-to-one relationship between the initial and study period scenario probabilities. The initial scenario probabilities are known, and the study period probabilities Π are calculated.

Study Period Scenario Probability Calculation

Calculating the probability of a study period scenario requires 10 steps. For some combinations of event durations and study period durations, the method may generate negative probabilities for study period scenarios. Steps 4, 6, and 9 of the method overcome this infeasibility by increasing the number (essentially the duration) of events in the study period to generate a feasible solution. Exhibit 37-19 shows the process flow of the proposed methodology.

Step 1: Select Initial Scenarios Associated with a Specific Demand Pattern

In this step, all combinations of weather and incident types associated with a given demand pattern are selected. The normal condition scenario typically has a large probability of occurrence relative to the other scenarios.

For example, the sample data in Exhibit 37-17 show five weather types (normal, medium rain, low visibility, light snow, and light–medium snow) and five incident types (no incident, shoulder closed, one lane closed, two lanes closed, and three lanes closed) associated with a given demand pattern. Exhibit 37-20 summarizes the probability of each of the combinations in the sample data. The sum of the probabilities of all of the initial scenarios is 14.176%. Therefore, the sum of the adjusted probabilities for the study period scenarios must also be 14.176%.

Exhibit 37-19
Probability Calculation Methodology for Study Period Scenarios

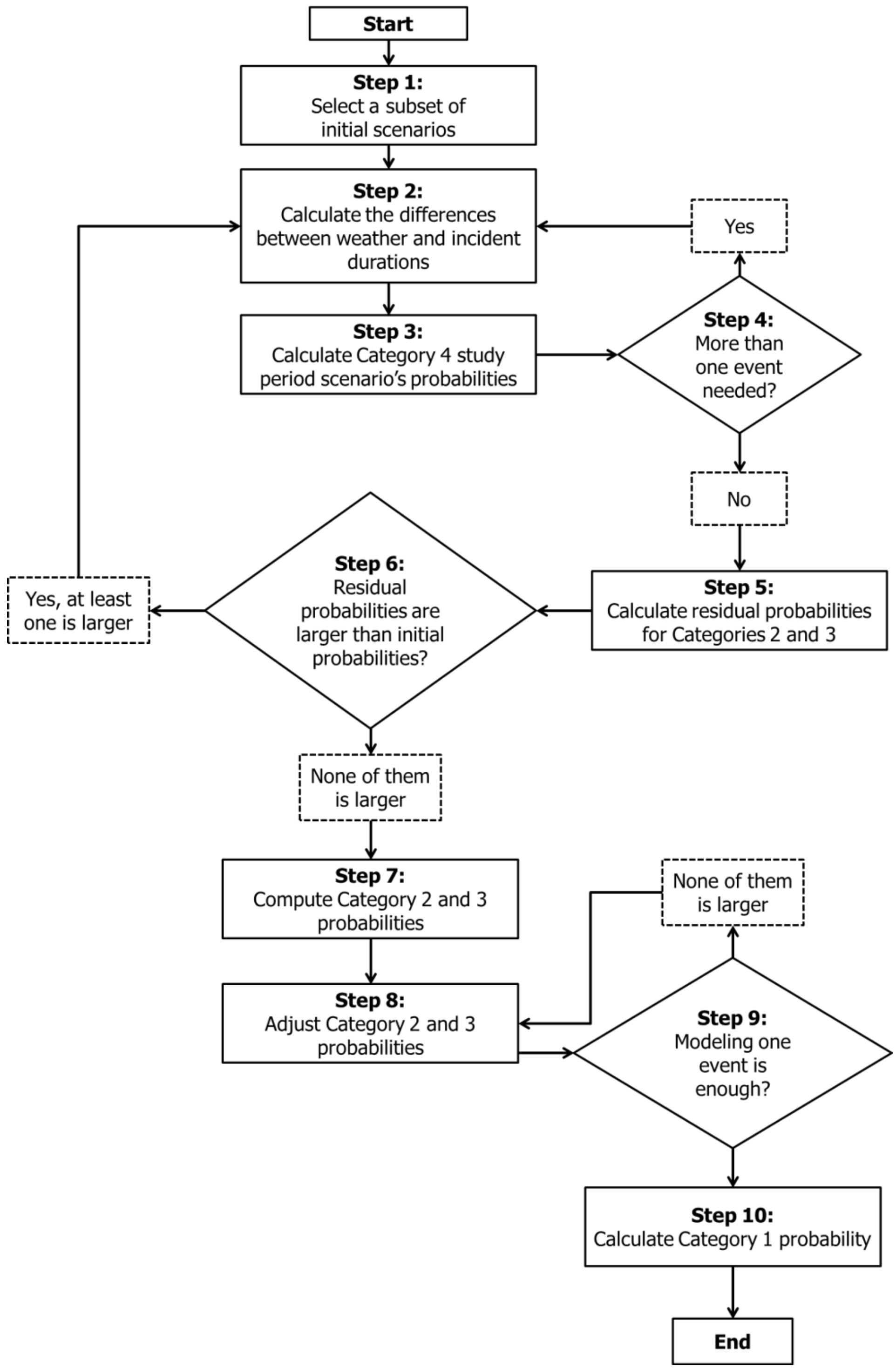


Exhibit 37-20
Example Combinations of Weather and Incidents Associated with a Demand Pattern

Incident Category *i*	Normal (%)	Medium Rain (%)	Low Visibility (%)	Light–Medium Snow (%)	Light Snow (%)	Total (%)
	Weather Category *w*					
No incident	8.84737	0.14309	0.06633	0.01666	0.44710	9.52054
Shoulder closed	3.00484	0.05025	0.02332	0.00531	0.14825	3.23197
1 lane closed	0.90935	0.01524	0.00707	0.00160	0.04479	0.97805
2 lanes closed	0.23029	0.00386	0.00179	0.00040	0.01134	0.24769
3 lanes closed	0.18409	0.00309	0.00143	0.00032	0.00906	0.19799
Total	13.17593	0.21553	0.09995	0.02430	0.66053	14.17625

Step 2: Calculate Time Differences Between Weather and Incident Event Durations

According to the definition of Category 4 initial scenarios (demand with weather and incidents), weather and incident events on the freeway facility have the same duration. In reality, they might have different durations. Therefore, this step compares the durations of weather and incident events and calculates the differences.

Modeling any weather or incident event requires its duration to be rounded to the length of the nearest analysis period length, or 15 min. The notation Round(t) is used to symbolize the value of t rounded to its nearest 15-min value.

The time that both weather and incident events occur ω_{wi} and the difference in weather and incident durations Δ_{wi} are calculated as follows for each Category 4 scenario:

Equation 37-17

$$\omega_{wi} = \min\left(\text{round}(\tau_w^{wea}), \text{round}\left(\tau_i^{inc}\right)\right)$$

Equation 37-18

$$\Delta_{wi} = \left|\text{round}(\tau_w^{wea}) - \text{round}\left(\tau_i^{inc}\right)\right|$$

where

ω_{wi} = time that both weather event w and incident event i occur in a Category 4 initial scenario (min),

Δ_{wi} = difference in duration between weather event w and incident event i (min),

τ_w^{wea} = duration of weather event w (min), and

τ_i^{inc} = duration of incident event i (min).

Step 3: Calculate Category 4 Study Period Scenario Probability

If only a single weather event coincides with a single incident event in a study period scenario, the relationship between the study period scenario's probability π_{wi} and the initial scenario's probability P_{wi} is in the following form:

Equation 37-19

$$P_{wi} = \pi_{wi} \times \left(\frac{\omega_{wi}}{t_{SP}}\right)$$

where t_{SP} is the study period duration in minutes.

This equation shows a one-to-one relationship between study period and initial scenario probabilities. It indicates that the probability of an initial scenario is the proportion of time that has the same condition during the study period multiplied by the probability of the study period scenario. Although the condition immediately after the event is not completely the same as the normal condition scenario (Category 1)—for example, the impact of wet pavement after a rain event has ended—that effect is ignored in the method. This bias is considered negligible. Equation 37-20 gives the probability of the study period scenarios as a function of the probability of the initial scenarios, where all variables are as previously defined.

$$\pi_{wi} = P_{wi} \times \left(\frac{t_{SP}}{\omega_{wi}}\right)$$

Equation 37-20

Step 4: Check Necessity for Modeling More Than One Event in Category 4 Scenarios

The sum of all probabilities generated in Step 3 for Category 4 scenarios should be less than the sum of the initial scenario probabilities. Otherwise, the study period scenarios would need more than one event per study period. Equation 37-21 provides a check for proceeding to Step 5 with no change in event durations:

$$\sum_{\substack{w=1 \text{ to } 10 \\ i=1 \text{ to } 5}} \pi_{wi} < \sum_{\substack{w=0 \text{ to } 10 \\ i=0 \text{ to } 5}} P_{wi}$$

Equation 37-21

where w and i represent the weather and incident types, respectively, and an index value of 0 represents the no-event condition (i.e., non–severe weather or no incident).

Should the constraint in Equation 37-21 not be met, the solution lies in modeling more than one incident and weather event simultaneously. Therefore, the process of modeling more than one event should be followed (i.e., increase the values of ω_{wi}), and Steps 2 and 3 should be repeated to make sure that the sum of all probabilities is low enough that the condition in Equation 37-21 is satisfied. Differences between weather and incident event durations should also be investigated. In some cases, repeating the shorter event (usually the incident), and thus modeling two incidents concurrent with one weather event, satisfies the condition. If any such changes are made, Steps 2 and 3 should be repeated.

Step 5: Calculate Residual Probabilities for Category 2 and 3 Scenarios

Residual probabilities are imposed by the differences in durations of the weather and incident events in Category 4 scenarios. In Step 3, the study period was modeled with weather and incident events together with common durations and probabilities. Because weather and incident events are likely to have different durations, the effect of the longer of the two events should be modeled to maintain accuracy.

Category 4 scenarios can be divided into three groups:

- Type *W* scenarios, where the rounded weather event duration is greater than the rounded incident event duration;
- Type *I* scenarios, where the rounded incident event duration is greater than the rounded weather event duration; and

- Type *N* scenarios, where the rounded weather and incident event durations are equal.

There is no need to compute the residual probabilities for Type *N* scenarios; therefore, the remainder of this step focuses on Type *W* and Type *I* scenarios.

In this step a portion of the probability of each demand-plus-weather scenario (Category 2) is assigned to the Type *W* scenarios, and a portion of the probability of demand-plus-incident (Category 3) scenarios is assigned to the Type *I* scenarios. This is because the study period scenarios generated in Step 3 do not represent merely Category 4 scenarios; portions of them also represent Category 2 or 3 scenarios (or both).

The probability residual of Category 4 scenarios assigned to Category 2 scenarios π'_w is calculated as follows:

Equation 37-22

$$\pi'_w = \sum_{i=1}^{5} \pi_{wi} \times \alpha_{wi} \times \left(\frac{\Delta_{wi}}{t_{SP}}\right)$$

where

π'_w = probability residual of Category 4 scenarios assigned to Category 2 scenarios,

π_{wi} = probability of study period scenario with weather type w and incident type i,

α_{ij} = 1 for Type *W* scenarios and 0 otherwise,

Δ_{wi} = difference in duration between weather event w and incident event i (min), and

t_{SP} = study period duration (min).

Similarly, the probability residual of Category 4 scenarios assigned to Category 3 scenarios π''_i is calculated as follows:

Equation 37-23

$$\pi''_i = \sum_{w=1}^{10} \pi_{wi} \times \beta_{wi} \times \left(\frac{\Delta_{wi}}{t_{SP}}\right)$$

where

π''_i = probability residual of Category 4 scenarios assigned to Category 3 scenarios,

π_{wi} = probability of study period scenario with weather type w and incident type i,

β_{ij} = 1 for Type *I* scenarios and 0 otherwise,

Δ_{wi} = difference in duration between weather event w and incident event i (min), and

t_{SP} = study period duration (min).

The α_{wi} and β_{wi} indicator variables are used to filter the Type *W* and *I* scenarios.

Step 6: Check That Residual Probabilities Are Lower Than Category 2 and 3 Initial Scenario Probabilities

If π'_w and π''_i are greater than the probability of Category 2 and 3 scenarios, the impact of the difference between the weather and incident event durations Δ_{wi} is larger than the impact of the expected demand-plus-weather or demand-plus-incident initial scenarios. In this case, the shorter event must be modeled with a longer duration in Step 3, and the procedure needs to be restarted from Step 3. Before Step 7 is undertaken, Equation 37-24 and Equation 37-25 must hold for all Category 2 and 3 scenarios:

$$\pi''_i < P_{wi} \quad w = 0$$ **Equation 37-24**

$$\pi'_w < P_{wi} \quad i = 0$$ **Equation 37-25**

Step 7: Calculate Remaining Probabilities of Category 2 and 3 Scenarios

This step calculates the remaining initial scenario probabilities for Category 2 and 3 study period scenarios. These probabilities represent the portion of initial scenario probabilities not modeled as part of Category 4 study period scenarios. Equation 37-26 provides the remaining probability for Category 2 scenarios p_{w0}, and Equation 37-27 provides the remaining probability for Category 3 scenarios p_{0i}.

$$p_{w0} = P_{wi} - \pi'_w$$ **Equation 37-26**

$$p_{0i} = P_{wi} - \pi''_i$$ **Equation 37-27**

where all variables are as defined previously. The check of probabilities in Step 6 ensures that the probabilities calculated in Step 7 are positive.

Step 8: Adjust Category 2 and 3 Probabilities

The adjusted probability of a Category 2 scenario π_{w0} is computed from Equation 37-28 by using the remaining probability of a Category 2 scenario determined in Step 7:

$$\pi_{w0} = p_{w0} \times \left(\frac{t_{SP}}{\mathrm{round}(\tau_w^{wea})} \right)$$ **Equation 37-28**

A similar process is used to calculate the adjusted probability of a Category 3 scenario π_{0i}:

$$\pi_{0i} = p_{0i} \times \left(\frac{t_{SP}}{\mathrm{round}(\tau_i^{inc})} \right)$$ **Equation 37-29**

Step 9: Check Necessity of Modeling More Than One Event per Study Period in Category 2 and 3 Scenarios

If the overall sum of probabilities for Category 2 through 4 scenarios is greater than the sum of the initial scenario probabilities, some Category 2 and 3 scenarios will need to have more than one event to have their probabilities match the initial scenario probabilities. This is because all the probabilities are time-based, and by increasing the duration, the probability can be reduced, as can be shown from Equation 37-28 and Equation 37-29.

Step 10: Calculate Category 1 Scenario Probability

The difference between the sum of probabilities of the initial scenarios and the current sum of probabilities for Category 2 through 4 study period scenarios is assigned to the Category 1 (normal condition) scenario.

OPERATIONAL SCENARIO GENERATION

Incident impacts on freeway facilities are sensitive to the facility geometry (e.g., number of lanes, segment type, and segment length) and the prevailing demand level. The effect of an incident on travel time could vary with demand, with greater impact anticipated when the facility is operating near capacity. Therefore, to capture the real effect of an incident on the freeway facility, an incident's location, start time, and duration are allowed to vary. The method assumes two possible incident start times (start and middle of the study period), three possible durations (25th, 50th, and 75th percentile), and three possible locations (first, middle, or last basic segment) on the facility.

Weather events are assumed to affect the entire facility at once, but their start times are allowed to vary. The method assumes two possible start times (start and middle of the study period) for a weather event and one event duration (the average).

Operational scenarios must be developed for each study period scenario. They must incorporate all of the combinations of start time, duration, and location applicable to a particular event type (weather or incident).

Operational Scenario Probabilities

The view of the system operator is taken in developing the travel time distribution. That is, the operator is interested in the aggregate performance of the facility over each 15-min analysis period during the reliability reporting period.

For the Category 1 (normal condition) scenario with an adjusted probability of π_{00} and a total number of analysis periods within the study period A, the facility travel time in each 15-min analysis period will be given a probability equal to π_{00} / A. For example, if the study period is 6 h long (24 analysis periods) and the adjusted Category 1 probability is 0.0084%, each analysis period will be given a probability of 0.0084% / 24 = 0.00035%.

For a Category 2 (demand-plus-weather) scenario with an adjusted probability of π_{w0}, the facility travel time for each analysis period will be given a probability equal to π_{w0} / (2 × A). The reason for the division by 2 is that two operational scenarios will be generated, with the weather event at the start of the study period in one and at the middle of the study period in the other.

For a Category 3 (demand-plus-incident) scenario with an adjusted probability of π_{0i}, the facility travel time for each analysis period will be given a probability equal to π_{0i} / (2 × 3 × 3 × A). Here, 18 operational scenarios will be generated, one for each combination of three locations, three durations, and two start times.

Finally, for a Category 4 (demand, weather, and incident) scenario with an adjusted probability of π_{wi}, the facility travel time for each analysis period will be given a probability equal to π_{wi} / (2 × 3 × 3 × A). A total of 18 operational scenarios will be generated, one for each combination of three incident locations, three incident durations, and two incident start times. Since severe weather starts at the same time as the incident, there is no need for an additional division by 2.

Postprocessing Operational Scenarios

Some operational scenarios may be infeasible, because a facility may not have the same number of cross-sectional lanes throughout. For example, in the process of varying the incident location, a scenario could result in a total segment closure, such as a two-lane closure on a two-lane segment. These infeasible scenarios are purged from the final list of operational scenarios, and their probabilities are reassigned proportionally to the remaining operational scenarios on the basis of their probability of occurrence.

Estimating the Maximum Number of Scenarios

Equation 37-30 can be used to estimate the number of operational scenarios that will be generated. Because of the merging of some demand patterns and the application of minimum thresholds for including a scenario, some weather and incident events could have a zero probability. The following is the total number of scenarios as a function of the various factors:

$$N = N_{\text{Demand}} + [N_{\text{Demand}} \times (N_{\text{Weather}} - 1)] \times C_{\text{Weather}} + [N_{\text{Demand}} \times (N_{\text{Incidents}} - 1)] \times C_{\text{Incidents}} + [N_{\text{Demand}} \times (N_{\text{Weather}} - 1) \times (N_{\text{Incidents}} - 1)] \times C_{\text{Incidents}} \times C_{\text{Weather}}$$

Equation 37-30

N denotes the total number of scenarios, while N_{Weather} and $N_{\text{Incidents}}$ are the weather categories (11) and incident categories (six) aggregated across demand patterns. Each incident category produces 18 operational scenarios ($C_{\text{Incidents}}$), while each weather scenario produces two operational scenarios (C_{Weather}). If the 12 default demand patterns are used, Equation 37-30 determines that a maximum of 22,932 operational scenarios will be generated. The actual number of operational scenarios generated could be up to an order of magnitude less.

MIGRATING SCENARIOS TO THE CHAPTER 10 METHOD

At this point, all of the operational scenarios have been specified. Next, each scenario specification is used to generate input data for the Chapter 10 freeway facilities procedure. The three basic types of information required are geometry, capacity, and demand data.

Geometric Information

The following is the necessary geometric information that is required for base conditions for the freeway facility:

- Segment types (basic, weave, merge, diverge),
- Segment lengths,
- Number of lanes for each segment, and
- Free-flow speed (mainline and ramps).

Two of these items can be altered in a given operational scenario: number of operational lanes and free-flow speed, depending on the type of weather or incident event that occurs in the scenario.

Demand Adjustments

Demand in Data-Poor Environments

When agencies have no access to detailed demand information for the freeway facility, daily demands are computed on the basis of AADT estimates for the facility, combined with day-of-week and month-of-year demand ratios. Since each operational scenario is associated with an initial scenario and each initial scenario is a combination of a demand pattern, weather event, and incident event, the initial scenario's demand pattern, multiplied by the appropriate demand ratio, is used to generate the demand for a given operational scenario.

Hourly variations supplied by the analyst are used to generate hourly demands from the daily demand in a given operational scenario. Linear interpolation is used to estimate 15-min analysis period demands, as shown in Equation 37-31.

Equation 37-31

$$(D_s^t)_k = \left(4 \times K_t^{15\text{min}}\right) \times (DR_k) \times \left(\frac{DAADT_s}{24}\right)$$

where

$(D_s^t)_k$ = hourly demand in segment s and analysis period t for operational scenario k (veh/h),

$K_t^{15\text{min}}$ = portion of demand in analysis period t,

DR_k = aggregated demand ratio for operational scenario k, and

$DAADT_s$ = directional AADT in segment s (veh).

The aggregation used for DR_k is based on the number of days that the demand pattern is in effect.

Demand in Data-Rich Environments

In a data-rich environment, hourly demand values for all analysis periods of a study period are provided through a detailed seed file. The only adjustment required is to include a daily demand multiplier for the seed study period DM_{Seed}. Then the hourly demand $(D_s^t)_k$ on segment s in time period t for operational scenario k is as follows:

Equation 37-32

$$(D_s^t)_k = \left(\frac{(D_s^t)_{\text{Seed}}}{DM_{\text{Seed}}}\right)(DR_k)$$

where all variables are as defined previously.

Capacity and Speed Adjustments

General Process

Modeling an incident or weather event on a freeway facility is done by (*a*) applying a CAF; (*b*) applying a SAF; and, in the case of a lane closure, (*c*) setting the number of operating lanes for the segment with the lane closure.

The scenario generator distinguishes between the capacity loss due to closed lanes and the frictional effect on the remaining open lanes. The former type of loss is specified through the number of operating lanes, while the latter type of loss is specified by the CAF for the incident or work zone.

Reductions in free-flow speed due to weather events are specified by the SAF associated with the weather event. There is no evidence in the literature that incidents affect the prevailing free-flow speed (*8*); therefore, a default value of 1.00 is used as the free-flow SAF for incidents.

The analyst may define local CAFs and SAFs for incident and weather events. Otherwise, the default values given in Exhibit 36-26 in Chapter 36, Travel Time Reliability, are used. When both weather and incident conditions are present, their respective CAFs and SAFs are multiplied together as follows:

$$CAF = CAF_i^{Inc} \times CAF_w^{Wea}$$

Equation 37-33

$$SAF = SAF_i^{Inc} \times SAF_w^{Wea}$$

Equation 37-34

where

CAF = capacity adjustment factor,

CAF_i^{Inc} = capacity adjustment factor for incident type i,

CAF_w^{Wea} = capacity adjustment factor for weather type w,

SAF = speed adjustment factor,

SAF_i^{Inc} = speed adjustment factor for incident type i, and

SAF_w^{Wea} = speed adjustment factor for weather type w.

These combined CAFs and SAFs are calculated for each segment and each analysis period.

Basic Freeway Segments

A modified version of Equation 25-1 from Chapter 25, Freeway Facilities: Supplemental, is used in combination with the combined CAFs and SAFs to predict basic freeway segment performance under incident and severe weather scenarios:

$$S = (FFS \times SAF) + \left[1 - e^{\ln\left((FFS \times SAF) + 1 - \frac{C \times CAF}{45}\right) \times \frac{v_p}{C \times CAF}}\right]$$

Equation 37-35

where

S = segment speed (mi/h),

FFS = segment free-flow speed (mi/h),

SAF = segment speed adjustment factor,

C = original segment capacity (pc/h/ln),

CAF = capacity adjustment factor, and

v_p = segment flow rate (pc/h/ln).

Merge, Diverge, and Weaving Segments

Equation 37-35 is ultimately intended for application to basic freeway segments. However, in both HCM2000 and HCM 2010, it is also applied to the analysis of merge/diverge and weaving segments with a CAF less than 1.0. The remainder of this section describes the adaptation of CAF and SAF to these HCM freeway segment types.

A challenge arises in both the merge/diverge and weaving methods when CAF and SAF are considered, since these methods do not use segment capacity as an input in the speed prediction equation. In essence, these methods violate the fundamental equation of traffic flow (speed = flow × density). Instead, both methods first estimate segment capacity and then perform a check to ensure that traffic demands are below that capacity (otherwise, the demand-to-capacity ratio is greater than 1 and the oversaturated module is invoked). If the segment passes the capacity check, the segment speed is estimated from an independent regression equation.

CAFs for Merge, Diverge, and Weaving Segments

For reliability analysis, the base capacity is adjusted with the appropriate CAF before the demand-to-capacity check is performed as follows:

Equation 37-36

$$\text{Adjusted Capacity} = \text{Base Capacity} \times \text{CAF}$$

where Adjusted Capacity is the capacity used to perform the demand-to-capacity check; Base Capacity is the merge/diverge or weaving segment capacity estimated from Chapter 12 or 13, respectively; and CAF is the capacity adjustment factor. SAF is subsequently applied as a multiplier of free-flow speed in the speed prediction equation, as discussed below for merge/diverge and weaving segments. The application of CAF and SAF is generally consistent with the basic segment procedure, but with the caveat that the factors are applied in two (or more) separate steps.

SAFs for Merge and Diverge Segments

Exhibit 13-11 gives equations for estimating the average speed of vehicles within the on-ramp influence area and in the outer lanes of the freeway. These equations are updated as shown in Exhibit 37-21 to incorporate the SAF. Similarly, the equations in Exhibit 13-12 for off-ramp influence areas are updated as shown in Exhibit 37-22.

Exhibit 37-21
Estimating Speed at On-Ramp (Merge) Junctions with SAF Consideration

Average Speed in	Equation	
Ramp influence area	$S_R = (FFS \times SAF) - ((FFS \times SAF) - 42)M_S$	
	$M_S = 0.321 + 0.0039e^{(v_{R12}/1,000)} - 0.002\ (L_A S_{FR} \times SAF / 1,000)$	
Outer lanes of freeway	$S_O = FFS \times SAF$	$v_{OA} < 500$ pc/h
	$S_O = (FFS \times SAF) - 0.0036(v_{OA} - 500)$	500 pc/h $\leq v_{OA} \leq$ 2,300 pc/h
	$S_O = (FFS \times SAF) - 6.53 - 0.006(v_{OA} - 2,300)$	$v_{OA} >$ 2,300 pc/h

Exhibit 37-22
Estimating Speed at Off-Ramp (Diverge) Junctions with SAF Consideration

Average Speed in	Equation	
Ramp influence area	$S_R = (FFS \times SAF) - ((FFS \times SAF) - 42)D_S$	
	$D_S = 0.883 + 0.00009v_R - 0.013(S_{FR} \times SAF)$	
Outer lanes of freeway	$S_O = 1.097(FFS \times SAF)$	$v_{OA} <$ 1,000 pc/h
	$S_O = 1.097(FFS \times SAF) - 0.0039\ (v_{OA} - 1,000)$	$v_{OA} \geq$ 1,000 pc/h

The variables used in Exhibit 37-21 and Exhibit 37-22 are as follows:

S_R = average speed of vehicles within the ramp influence area (mi/h); for merge areas, this includes all ramp and freeway vehicles in Lanes 1 and 2; for diverge areas, this includes all vehicles in Lanes 1 and 2;

S_O = average speed of vehicles in outer lanes of the freeway, adjacent to the 1,500-ft ramp influence area (mi/h);

FFS = free-flow speed of the freeway (mi/h);

SAF = speed adjustment factor for the ramp segment (decimal);

S_{FR} = free-flow speed of the ramp (mi/h);

L_A = length of acceleration lane (ft);

v_R = demand flow rate on ramp (pc/h);

v_{R12} = total demand flow rate entering the on-ramp influence area, including v_R and the demand flow rate in Lanes 1 and 2 of the freeway immediately upstream of the ramp influence area (pc/h);

v_{OA} = average demand flow per lane in outer lanes adjacent to the ramp influence area (not including flow in Lanes 1 and 2) (pc/h/ln);

M_S = speed index for on-ramps (merge areas); this is simply an intermediate computation that simplifies the equations; and

D_S = speed index for off-ramps (diverge areas); this is simply an intermediate computation that simplifies the equations.

SAFs for Weaving Segments

The equations for calculating the speed of weaving and nonweaving vehicles in weaving segments (Equations 12-18 through 12-20) are modified by multiplying each occurrence of FFS by SAF, and the space mean speed of all vehicles in the weaving segment (Equation 12-21) is now computed by using the adjusted values of weaving and nonweaving vehicle speeds:

Equation 37-37

$$S_W = 15 + \left(\frac{(FFS \times SAF) - 15}{1 + W}\right)$$

Equation 37-38

$$W = 0.226\left(\frac{LC_{ALL}}{L_S}\right)^{0.789}$$

Equation 37-39

$$S_{NW} = (FFS \times SAF) - (0.0072 LC_{MIN}) - \left(0.0048\frac{v}{N}\right)$$

Equation 37-40

$$S = \frac{v_W + v_{NW}}{\left(\frac{v_W}{S_W}\right) + \left(\frac{v_{NW}}{S_{NW}}\right)}$$

where

S_W = average speed of weaving vehicles within the weaving segment (mi/h);

S_{NW} = average speed of nonweaving vehicles within the weaving segment (mi/h);

FFS = free-flow speed of the weaving segment (mi/h);

SAF = speed adjustment factor for the weaving segment (decimal);

W = weaving intensity factor;

L_S = weaving segment length (ft);

LC_{ALL} = total lane-changing rate of all vehicles in the weaving segment, from Chapter 12 (lc/h);

LC_{MIN} = minimum rate of lane changing that must exist for *all* weaving vehicles to complete their weaving maneuvers successfully, from Chapter 12 (lc/h);

v = total demand flow rate in the weaving segment = $v_W + v_{NW}$ (pc/h);

N = number of lanes within the weaving section;

S = space mean speed of all vehicles in the weaving segment (mi/h);

v_W = weaving demand flow rate in the weaving segment (pc/h); and

v_{NW} = nonweaving demand flow rate in the weaving segment (pc/h).

4. URBAN STREET SCENARIO GENERATION

WEATHER EVENT PREDICTION

The weather event procedure is used to predict weather events during the reliability reporting period. The events predicted include rainfall and snowfall. The time following each event that the pavement remains wet or covered by snow or ice is also predicted. The presence of these conditions has been found to influence running speed and intersection saturation flow rate.

The weather event procedure consists of a series of calculation steps. The calculations associated with each step are described in the following paragraphs. A random number is used in several of the steps. All random numbers have a real value that is uniformly distributed from 0.0 to 1.0.

Step 1: Precipitation Prediction

The probability of precipitation for any given day is computed by using the following equation.

$$P(precip)_m = \frac{Ndp_m}{Nd_m}$$

Equation 37-41

where

$P(precip)_m$ = probability of precipitation in any given day of month m,

Ndp_m = number of days with precipitation of 0.01 in. or more in month m (days), and

Nd_m = total number of days in month m (days).

For each day considered, the following rule is checked to determine whether precipitation occurs:

$$\text{No precipitation if } Rp_d \geq P(precip)_d$$
$$\text{Precipitation if } Rp_d < P(precip)_d$$

Equation 37-42

where

$P(precip)_d$ = probability of precipitation for day d, and

Rp_d = random number for precipitation for day d.

Step 2: Precipitation Type

If precipitation occurs, the following equation is used to estimate the average temperature during the weather event for the subject day.

$$T_{d,m} = normal^{-1}(p = Rg_d,\ \mu = \bar{T}_m, \sigma = s_T)$$

Equation 37-43

where

$T_{d,m}$ = average temperature for day d of month m (°F),

Rg_d = random number for temperature for day d,

$\bar{T}_m$ = normal daily mean temperature in month m (°F),

s_T = standard deviation of daily mean temperature in a month (= 5.0) (˚F), and

$normal^{-1}(p, \mu, \sigma)$ = value associated with probability p for a cumulative normal distribution with mean μ and standard deviation σ.

The average temperature for the day is used to determine whether the precipitation is in the form of rain or snow. The following rule is checked to determine whether the precipitation that day is in the form of rain or snow.

Equation 37-44

$$\text{Rain if } T_{d.m} \geq 32°\text{F}$$
$$\text{Snow if } T_{d,m} < 32°\text{F}$$

Step 3: Rain Intensity

The following equation is used to estimate the rainfall rate during a rain event.

Equation 37-45

$$rr_{d,m} = gamma^{-1}\left(p = Rr_d,\ \mu = \overline{rr}_m,\ \sigma = s_{rr,m}\right)$$

where

$rr_{d,m}$ = rainfall rate for the rain event occurring on day d of month m (in./h),

Rr_d = random number for rainfall rate for day d,

$\overline{rr}_m$ = precipitation rate in month m (in./h),

$s_{rr,m}$ = standard deviation of precipitation rate in month m (= 1.0 $\overline{rr}_m$) (in./h), and

$gamma^{-1}(p, \mu, \sigma)$ = value associated with probability p for a cumulative gamma distribution with mean μ and standard deviation σ.

The average precipitation rate (and its standard deviation) is based on time periods when precipitation is falling. Thus, the average precipitation rate represents an average for all hours for which precipitation is falling (and excluding any hours when precipitation is not falling).

The following equation is used to estimate the total amount of rainfall for a rain event. It is assumed here that there is one rain event for each day with precipitation.

Equation 37-46

$$tr_{d,m} = gamma^{-1}\left(p = Rt_d,\ \mu = \overline{tr}_m,\ \sigma = s_{tr,m}\right)$$

with

Equation 37-47

$$\overline{tr}_m = \frac{tp_m}{Ndp_m}$$

Equation 37-48

$$s_{tr,m} = \min(2.5\overline{tr}_m, 0.65)$$

where

$tr_{d,m}$ = total rainfall for the rain event occurring on day d of month m (in./event),

Rt_d = random number for rainfall total for day d (= Rr_d),

$\overline{tr}_m$ = average total rainfall per event in month m (in./event),

$s_{tr,m}$ = standard deviation of total rainfall in month m (in./event),

tp_m = total normal precipitation for month m (in.), and

Ndp_m = number of days with precipitation of 0.01 in. or more in month m (days).

Total rainfall for a rain event is the product of rainfall rate and rain event duration. Thus, the total rainfall amount is highly correlated with the rainfall rate. For reliability evaluation, total rainfall is assumed to be perfectly correlated with rainfall rate such that they share the same random number. This approach may result in slightly less variability in the estimated total rainfall; however, it precludes the occasional calculation of unrealistically long or short rain events.

Step 4: Rainfall Duration

The following equation is used to estimate the rainfall duration for a rain event:

$$dr_{d,m} = \frac{tr_{d,m}}{rr_{d,m}}$$

Equation 37-49

where

$dr_{d,m}$ = rainfall duration for the rain event occurring on day d of month m (h/event),

$tr_{d,m}$ = total rainfall for the rain event occurring on day d of month m (in./event), and

$rr_{d,m}$ = rainfall rate for the rain event occurring on day d of month m (in./h).

The duration computed with Equation 37-49 is used in a subsequent step to determine whether an analysis period is associated with a rain event. To simplify the analysis in this subsequent step, it is assumed that no rain event extends beyond midnight. To ensure this outcome, the duration computed from Equation 37-49 is compared with the time duration between the start of the study period and midnight. The rainfall duration is then set to equal the smaller of these two values.

Step 5: Start Time of Weather Event

The hour of the day that the rain event starts is determined randomly. The start hour is computed with the following equation.

$$ts_{d,m} = (24 - dr_{d,m})R_{s,d}$$

Equation 37-50

where

$ts_{d,m}$ = start of rain event on day d of month m (h),

24 = number of hours in a day (h/day),

$dr_{d,m}$ = rainfall duration for the rain event occurring on day d of month m (h/event), and

$R_{s,d}$ = random number for rain event start time for day d.

The start time from Equation 37-50 is rounded to the nearest hour for 1-h analysis periods, or to the nearest quarter hour for 15-min analysis periods.

Step 6: Wet Pavement Duration

After a rain event, the pavement typically remains wet for some length of time. The presence of wet pavement can influence road safety by reducing surface–tire friction. Research (*9*) indicates that wet pavement time can be computed with the following equation.

Equation 37-51

$$dw_{d,m} = dr_{d,m} + do_{d,m} + dd_{d,m}$$

with

Equation 37-52

$$dd_{d.m} = 0.888\ \exp\left(-0.0070T_{d,m}\right) + 0.19I_{\text{night}}$$

where

$dw_{d,m}$ = duration of wet pavement for rain event occurring on day d of month m (h/event),

$dr_{d,m}$ = rainfall duration for the rain event occurring on day d of month m (h/event),

$do_{d,m}$ = duration of pavement runoff for rain event occurring on day d of month m (= 0.083) (h/event),

$T_{d,m}$ = average temperature for day d of month m (°F),

I_{night} = indicator variable for day/night (= 0.0 if rain starts between 6:00 a.m. and 6:00 p.m., 1.0 otherwise), and

$dd_{d,m}$ = duration of drying time for rain event occurring on day d of month m (h/event).

The duration computed with Equation 37-51 is used in a subsequent step to determine whether an analysis period is associated with wet pavement conditions. To simplify the analysis in this subsequent step, it is assumed that no rain event extends beyond midnight. To ensure this outcome, the duration computed from Equation 37-51 is compared with the duration between the start of the rain event and midnight. The wet pavement duration is then set to equal the smaller of these two values.

Step 7: Snow Intensity and Duration

The snowfall rate (i.e., intensity) and duration are computed by using the calculation sequence in Steps 3 to 6. The equations are the same. The average snowfall rate and average snow total per event are computed by multiplying the average precipitation rate and average total rainfall per event, respectively, by the ratio of snow depth to rain depth. This ratio is estimated at 10 in./in on the basis of an analysis of weather data reported by the National Climatic Data Center (*10*).

In Step 6, the duration of pavement runoff is defined differently when it is applied to snow events. Specifically, it is defined as the time after the snow stops falling that snowpack (or ice) covers the pavement. After this period elapses, the pavement is exposed and drying begins. A default value for this variable is provided in Section 5, Applications, in Chapter 36.

Step 8: Identify Analysis Period Weather

Steps 1 through 7 are repeated for each day of a 2-year period, starting with the first day of the reliability reporting period. This 2-year record of weather events is used in the traffic incident procedure to estimate the weather-related incident frequency.

The days that have weather events are subsequently examined to determine whether the event occurs during the study period. Each analysis period is examined to determine whether it is associated with a weather event. If the pavement is wet during an analysis period, the precipitation type (i.e., rain or snow) is recorded for that period. If precipitation is falling, the precipitation rate is also recorded.

The durations of precipitation and wet pavement from Equation 37-49 and Equation 37-51, respectively, are rounded to the nearest hour for 1-h analysis periods or to the nearest quarter hour for 15-min analysis periods. The rounding is performed to ensure the most representative match between event duration and analysis period start and end times.

TRAFFIC DEMAND VARIATION PREDICTION

The traffic demand variation procedure is used to identify the appropriate traffic demand adjustment factors for each analysis period in the reliability reporting period. One set of factors accounts for systematic volume variation by hour of day, day of week, and month of year. Default values for these factors are provided in Section 5, Applications, in Chapter 36.

A random variation adjustment factor is also available and can be included, if desired, by the analyst. It accounts for the random variation in volume that occurs among 15-min time periods. This factor is described in more detail in the Scenario Dataset Generation section.

The procedure includes two adjustment factors to account for a reduction in traffic demand during inclement weather. One factor addresses demand change during periods of rainfall. The second factor addresses demand change during periods of snowfall. Default values for these factors are provided in Section 5, Applications, in Chapter 36.

This procedure does not address traffic diversion due to the presence of work zones or special events. Their accommodation in a reliability evaluation is discussed in the Analysis Techniques subsection of Section 4, Urban Street Methodology, in Chapter 36.

If the traffic volumes provided in the base dataset and the alternative datasets are computed by using planning procedures, the volumes in the dataset are based on the average day of week and month of year. In this situation, the adjustment factors for day of week and month of year are set to a value of 1.0.

The factors identified in this procedure are subsequently used in the scenario dataset generation procedure to compute the demand volume for the subject urban street facility.

TRAFFIC INCIDENT PREDICTION

The traffic incident procedure is used to predict incident date, time, and duration. It also determines incident event type (i.e., crash or noncrash), severity level, and location on the facility. Location is defined by the specific intersection or segment on which the incident occurs and whether the incident occurs on the shoulder, one lane, or multiple lanes. The procedure uses weather event and traffic demand variation information from the previous procedures in the incident prediction process.

The traffic incident procedure consists of a set of calculation steps. The calculations associated with each step are described in the following paragraphs. A random number is used in several of the steps. All random numbers have a real value that is uniformly distributed from 0.0 to 1.0.

Step 1: Compute the Equivalent Crash Frequency for Weather

Crash frequency increases when the road is wet, covered by snow, or covered by ice. The effect of weather on crash frequency is incorporated in the reliability methodology by converting the input crash frequency data into an equivalent crash frequency for each type of weather condition. The equivalent crash frequency for dry pavement conditions is defined by using the following equation:

Equation 37-53

$$Fc_{str(i),\mathrm{dry}} = \frac{Fc_{str(i)}8{,}760Ny}{Nh_{\mathrm{dry}} + CFAF_{rf}Nh_{rf} + CFAF_{wp}Nh_{wp} + CFAF_{sf}Nh_{sf} + CFAF_{sp}Nh_{sp}}$$

where

$Fc_{str(i),\mathrm{dry}}$ = equivalent crash frequency when every day is dry for street location i of type str (str = int: intersection, seg: segment) (crashes/year),

$Fc_{str(i)}$ = expected crash frequency for street location i of type str (crashes/year),

8,760 = number of hours in a year (h/year),

Ny = total number of years (years),

Nh_{dry} = total number of hours in Ny years with dry conditions (h),

Nh_{rf} = total number of hours in Ny years with rainfall conditions (h),

Nh_{wp} = total number of hours in Ny years with wet pavement and not raining (h),

Nh_{sf} = total number of hours in Ny years with snowfall conditions (h),

Nh_{sp} = total number of hours in Ny years with snow or ice on pavement and not snowing (h),

$CFAF_{rf}$ = crash frequency adjustment factor for rainfall,

$CFAF_{wp}$ = crash frequency adjustment factor for wet pavement (not raining),

$CFAF_{sf}$ = crash frequency adjustment factor for snowfall, and

$CFAF_{sp}$ = crash frequency adjustment factor for snow or ice on pavement (not snowing).

The equivalent crash frequency for nondry conditions is computed with the following equation. The crash frequency adjustment factor (CFAF) for dry weather $CFAF_{str(i),\mathrm{dry}}$ is 1.0.

$$Fc_{str(i),wea} = Fc_{str(i),\mathrm{dry}} CFAF_{wea}$$

Equation 37-54

where

$Fc_{str(i),wea}$ = equivalent crash frequency when every day has weather condition *wea* (*wea* = *dry*: no precipitation and dry pavement, *rf*: rainfall, *wp*: wet pavement but not raining, *sf*: snowfall, *sp*: snow or ice on pavement but not snowing) for street location *i* of type *str* (crashes/year);

$Fc_{str(i),\mathrm{dry}}$ = equivalent crash frequency when every day is dry for street location *i* of type *str* (crashes/year); and

$CFAF_{wea}$ = crash frequency adjustment factor for weather condition *wea.*

Equation 37-53 requires the total number of hours for each weather condition in the vicinity of the subject facility. A weather history that extends for 2 or more years should be used to reduce the random variability in the data. These hours can be obtained from available weather records or estimated by using the weather event procedure.

This step is applied separately to each intersection and segment on the facility. In applications to intersections, the expected crash frequency Fc is provided by the analyst for the subject intersection. In applications to segments, the expected crash frequency is provided by the analyst for the subject segment.

The CFAF is the ratio of hourly crash frequency during the weather event to the hourly crash rate during clear, dry hours. It is computed by using 1 or more years of historical weather data and crash data for the region in which the subject facility is located. Default values for these factors are provided in Section 5, Applications, in Chapter 36.

Step 2: Establish the CFAFs for Work Zones and Special Events

If the analysis period occurs during a work zone or special event, the CFAF variable for segments $CFAF_{str}$ and the CFAF variable for intersections $CFAF_{int}$ are set equal to the values provided by the analyst. Otherwise, $CFAF_{str}$ and $CFAF_{int}$ equal 1.0. This step is repeated for each analysis period of the reliability reporting period.

Step 3: Determine Whether an Incident Occurs

During this step, each of the 24 h in the subject day is examined to determine whether an incident occurs. The analysis considers each street location (i.e., intersection and segment) separately. At each street location, each of the following 12 incident types is addressed separately. Each of these types is considered separately for each hour of the day (whether the hour coincides with an analysis period is determined in a subsequent step).

- Crash, one lane blocked, fatal or injury;
- Crash, two or more lanes blocked, fatal or injury;
- Crash, shoulder location, fatal or injury;
- Crash, one lane blocked, property damage only;
- Crash, two or more lanes blocked, property damage only;
- Crash, shoulder location, property damage only;
- Noncrash, one lane blocked, breakdown;
- Noncrash, two or more lanes blocked, breakdown;
- Noncrash, shoulder location, breakdown;
- Noncrash, one lane blocked, other;
- Noncrash, two or more lanes blocked, other; and
- Noncrash, shoulder location, other.

"Other" refers to any kind of nonbreakdown incident (e.g., spill, dropped load).

Initially, the weather event data are checked to determine whether the subject day and hour are associated with rainfall, wet pavement and not raining, snowfall, or snow or ice on pavement and not snowing. For a given day, street location, and hour of day, the average incident frequency is computed by using the following equation based on the weather present at that hour and day.

Equation 37-55

$$Fi_{str(i),wea(h,d)} = CFAF_{str}\frac{Fc_{str(i),wea}}{pc_{str,wea}}$$

where

$Fi_{str(i),wea(h,d)}$ = expected incident frequency for street location *i* of type *str* and weather condition *wea*(*h*, *d*) during hour *h* and day *d* (incidents/year);

$CFAF_{str}$ = crash frequency adjustment factor for street location type *str*;

$Fc_{str(i),wea}$ = equivalent crash frequency when every day has weather condition *wea* for street location *i* of type *str* (crashes/year); and

$pc_{str,wea}$ = proportion of incidents that are crashes for street location type *str* and weather condition *wea*.

Default values for the proportion of incidents are provided in Section 5, Applications, in Chapter 36.

The incident frequency is converted to an hourly frequency that is sensitive to traffic demand variation by hour of day, day of week, and month of year. The frequency is computed with the following equation.

$$fi_{str(i),wea(h,d),h,d} = \frac{Fi_{str(i),wea(h,d)}}{8{,}760}\left(24 f_{hod,h,d}\right) f_{dow,d} f_{moy,d}$$

Equation 37-56

where

$fi_{str(i),wea(h,d),h,d}$ = expected hourly incident frequency for street location i of type str and weather condition $wea(h, d)$ during hour h and day d (incidents/h),

$Fi_{str(i),wea(h,d)}$ = expected incident frequency for street location i of type str and weather condition $wea(h, d)$ during hour h and day d (incidents/year),

8,760 = number of hours in a year (h/year),

24 = number of hours in a day (h/day),

$f_{hod,h,d}$ = hour-of-day adjustment factor based on hour h and day d,

$f_{dow,d}$ = day-of-week adjustment factor based on day d, and

$f_{moy,d}$ = month-of-year adjustment factor based on day d.

The hour-of-day adjustment factor includes a day subscript because its values depend on whether the day occurs during a weekday or a weekend. The day subscript for the day-of-week factor is used to determine which of the 7 weekdays is associated with the subject day. Similarly, the month subscript is used to determine which of the 12 months is associated with the subject day for the month-of-year factor. Default values for these adjustment factors are provided in Section 5, Applications, in Chapter 36.

Incidents for a given day, street location, incident type, and hour of day are assumed to follow a Poisson distribution. For any given combination of conditions, the probability of more than one incident of a given type is negligible, which reduces the question of whether an incident occurs to whether there are zero incidents or one incident of a given type. Equation 37-57 is used to compute the probability of no incidents occurring. Default values for the proportion of incidents are provided in Section 5, Applications, in Chapter 36.

$$p0_{str(i),wea(h,d),con,lan,sev,h,d} = \exp\left(-fi_{str(i),wea(h,d),h,d} \times pi_{str,wea(h,d),con,lan,sev}\right)$$

Equation 37-57

where

$p0_{str(i),wea(h,d),con,lan,sev,h,d}$ = probability of no incident for street location i of type str, weather condition $wea(h, d)$ during hour h and day d, event type con (con = cr: crash, nc: noncrash), lane location lan (lan = $1L$: one lane, $2L$: two or more lanes, sh: shoulder), and severity sev (sev = pdo: property damage only, fi: fatal or injury, bkd: breakdown, oth: other);

$fi_{str(i),wea(h,d),h,d}$ = expected hourly incident frequency for street location i of type str and weather condition $wea(h, d)$ during hour h and day d (incidents/h); and

$pi_{str,wea(h,d),con,lan,sev}$ = proportion of incidents for street location type *str*, weather condition *wea*(*h*, *d*) during hour *h* and day *d*, event type *con*, lane location *lan*, and severity *sev*.

The following rule is checked to determine whether the incident of a specific type occurs.

Equation 37-58

$$\text{No incident if } Ri_{str(i),wea(h,d),con,lan,sev,h,d} \leq p0_{str(i),wea(h,d),con,lan,sev,h,d}$$
$$\text{Incident if } Ri_{str(i),wea(h,d),con,lan,sev,h,d} > p0_{str(i),wea(h,d),con,lan,sev,h,d}$$

where

$Ri_{str(i),wea(h,d),con,lan,sev,h,d}$ = random number for incident for street location *i* of type *str*, weather condition *wea*(*h*, *d*) during hour *h* and day *d*, event type *con*, lane location *lan*, and severity *sev*; and

$p0_{str(i),wea(h,d),con,lan,sev,h,d}$ = probability of no incident for street location *i* of type *str*, weather condition *wea*(*h*, *d*) during hour *h* and day *d*, event type *con* (*con* = *cr*: crash, *nc*: noncrash), lane location *lan*, and severity *sev*.

Step 4: Determine Incident Duration

If the result of Step 3 indicates that an incident occurs for a given day, street location, incident type, and hour of day, then the calculations in this step are used to determine the incident duration. Each hour of the day is considered separately in this step.

Incident duration includes the incident detection time, response time, and clearance time. Research indicates that these values can vary by weather condition, event type, lane location, and severity. Default values for average incident duration are provided in Section 5, Applications, in Chapter 36.

The following equation is used to estimate the incident duration for a given incident:

Equation 37-59

$$di_{str(i),wea(h,d),con,lan,sev,h,d} = gamma^{-1}\begin{pmatrix} p = Rd_{str(i),con,lan,sev,h,d}, \\ \mu = \overline{di}_{str,wea(h,d),con,lan,sev}, \\ \sigma = s_{str,wea(h,d),con,lan,sev} \end{pmatrix}$$

where

$di_{str(i),wea(h,d),con,lan,sev,h,d}$ = incident duration for street location *i* of type *str*, weather condition *wea*(*h*, *d*) during hour *h* and day *d*, event type *con*, lane location *lan*, and severity *sev* (h);

$Rd_{str(i),con,lan,sev,h,d}$ = random number for incident duration for street location *i* of type *str* for hour *h* and day *d*, event type *con*, lane location *lan*, and severity *sev*;

$\overline{di}_{str(i),wea(h,d),con,lan,sev}$ = average incident duration for street location type *str*, weather condition *wea*(*h*, *d*) during hour *h* and day *d*, event type *con*, lane location *lan*, and severity *sev* (h);

$s_{str(i),wea(h,d),con,lan,sev}$ = standard deviation of incident duration for street location type *str*, weather condition *wea*(*h*, *d*) during hour h and day d, event type con, lane location lan, and severity sev (= 0.8 $\overline{di}_{str(i),wea(h,d),con,lan,sev}$) (h); and

$gamma^{-1}(p, \mu, \sigma)$ = value associated with probability p for cumulative gamma distribution with mean μ and standard deviation σ.

The duration computed with Equation 37-59 is used in a subsequent step to determine whether an analysis period is associated with an incident. To simplify the computations in this subsequent step, it is assumed that no incident extends beyond midnight. To ensure this outcome, the duration computed from Equation 37-59 is compared with the time duration between the start of the study period and midnight. The incident duration is then set to equal the smaller of these two values.

Step 5: Determine Incident Location

If the result of Step 3 indicates that an incident occurs for a given day, street location, incident type, and hour of day, then the calculations in this step are used to determine the incident location. For intersections, the location is one of the intersection legs. For segments, the location is one of the two travel directions. The location algorithm is volume-based so that the correct location determinations are made when three-leg intersections or one-way streets are addressed. Each hour of the day is considered separately in this step.

Intersection Location

When a specific intersection is associated with an incident, the location of the incident is based on consideration of each intersection leg volume lv. This volume represents the sum of all movements entering the intersection on the approach lanes and those exiting the intersection on the adjacent departure lanes. In the field, this volume would be measured by establishing a reference line from outside curb to outside curb on the subject leg (near the crosswalk) and counting all vehicles that cross the line, regardless of travel direction.

The leg volumes are summed, starting with the leg associated with NEMA Phase 2, to produce a cumulative volume by leg. The volumes are then converted to a proportion by dividing by the sum of the leg volumes. The calculation of these proportions is described by the following equations. One set of proportions is determined for the base dataset and for each work zone and special event dataset.

Equation 37-60

$$pv_{int(i),2} = lv_{int(i),2} / \left(2tv_{int(i)}\right)$$
$$pv_{int(i),4} = pv_{int(i),2} + lv_{int(i),4} / \left(2tv_{int(i)}\right)$$
$$pv_{int(i),6} = pv_{int(i),4} + lv_{int(i),6} / \left(2tv_{int(i)}\right)$$
$$pv_{int(i),8} = 1.0$$

with

Equation 37-61

$$tv_{int(i)} = \sum_{j=1}^{12} v_{\text{input},int(i),j}$$

where

$pv_{int(i),n}$ = cumulative sum of volume proportions for leg associated with NEMA phase n (n = 2, 4, 6, 8) at intersection i,

$lv_{int(i),n}$ = leg volume (two-way total) for leg associated with NEMA phase n at intersection i (veh/h),

$tv_{int(i)}$ = total volume entering intersection i (veh/h), and

$v_{\text{input},int(i),j}$ = movement j volume at intersection i (from dataset) (veh/h).

The leg location of the incident is determined by comparing a random number with the cumulative volume proportions. With this technique, the likelihood of an incident being assigned to a leg is proportional to its volume, relative to the other leg volumes. The location is determined for a given intersection i by the following rule.

Equation 37-62

$$\text{Incident on Phase 2 if } Rv_{int(i),con,lan,sev} \leq pv_{int(i),2}$$

$$\text{Incident on Phase 4 if } pv_{int(i),2} < Rv_{int(i),con,lan,sev} \leq pv_{int(i),4}$$

$$\text{Incident on Phase 6 if } pv_{int(i),4} < Rv_{int(i),con,lan,sev} \leq pv_{int(i),6}$$

$$\text{Incident on Phase 8 if } pv_{int(i),6} < Rv_{int(i),con,lan,sev} \leq pv_{int(i),8}$$

where

$Rv_{int(i),con,lan,sev}$ = random number for leg volume for intersection i, event type con, lane location lan, and severity sev; and

$pv_{int(i),n}$ = cumulative sum of volume proportions for leg associated with NEMA phase n (n = 2, 4, 6, 8) at intersection i.

Segment Location

When a specific segment is associated with an incident, the location of the incident is based on consideration of the volume in each direction of travel dv. This volume is computed by using the movement volume at the boundary intersection that uses NEMA Phase 2 to serve exiting through vehicles. The volume in the Phase 2 direction is computed as the sum of the movements exiting the segment at the boundary intersection (i.e., it equals the approach lane volume). The volume in the Phase 6 direction is computed as the sum of the movements entering the segment at the boundary intersection (i.e., it equals the departure lane volume). The two directional volumes are referenced to NEMA Phases 2 and 6. The sum of these two volumes equals the Phase 2 leg volume described in the previous subsection.

A cumulative volume proportion by direction is used to determine incident location. The calculation of these proportions is described by the following equations. One set of proportions is determined for the base dataset and for each work zone and special event dataset.

$$pv_{seg(i),2} = dv_{seg(i),2} / \left(dv_{seg(i),2} + dv_{seg(i),6} \right)$$
$$pv_{seg(i),6} = 1.0$$

Equation 37-63

where

$pv_{seg(i),n}$ = volume proportion for the direction of travel served by NEMA phase n (n = 2, 6) on segment i, and

$dv_{seg(i),n}$ = directional volume for the direction of travel served by NEMA phase n on segment i (veh/h).

The segment location of the incident is determined by comparing a random number with the cumulative volume proportions. With this technique, the likelihood of an incident being assigned to a direction of travel is proportional to its volume, relative to the volume in the other direction. The location is determined for a given segment i by the following rule.

$$\text{Incident in Phase 2 direction if } Rv_{seg(i),con,lan,sev} \leq pv_{seg(i),2}$$
$$\text{Incident in Phase 6 direction if } pv_{seg(i),2} < Rv_{seg(i),con,lan,sev} \leq pv_{seg(i),6}$$

Equation 37-64

where

$Rv_{seg(i),con\ lan,sev}$ = random number for volume for segment i, event type con, lane location lan, and severity sev; and

$pv_{seg(i),n}$ = volume proportion for the direction of travel served by NEMA phase n (n = 2, 6) on segment i.

Step 6: Identify Analysis Period Incidents

Steps 3 through 5 are repeated for each hour of the subject day. As implied by the discussion to this point, all incidents are assumed to occur at the start of a given hour.

During this step, the analysis periods associated with an incident are identified. Specifically, each hour of the study period is examined to determine whether it coincides with an incident. If an incident occurs, its event type, lane location, severity, and street location are identified and recorded. Each subsequent analysis period coinciding with the incident is also recorded.

The incident duration from Equation 37-59 is rounded to the nearest hour for 1-h analysis periods or to the nearest quarter hour for 15-min analysis periods. This rounding is performed to ensure the most representative match between event duration and analysis period start and end times.

SCENARIO DATASET GENERATION

The scenario dataset generation procedure uses the results from the preceding three procedures to develop one HCM dataset for each analysis period in the reliability reporting period. As discussed previously, each analysis period is considered to be one scenario.

This procedure creates a new dataset for each analysis period. The HCM dataset is modified to reflect conditions present during a given analysis period. Modifications are made to the traffic volumes at each intersection and driveway and to the saturation flow rate at intersections influenced by an incident or a weather event. The speed is also adjusted for segments influenced by an incident or a weather event.

The incident history developed by the traffic incident procedure is consulted during this procedure to determine whether an incident occurs at an intersection or on a segment. If an incident occurs at an intersection, the incident lane location data are consulted to determine which approach and movements are affected. If the incident occurs on the shoulder, the shoulder in question is assumed to be the outside shoulder (as opposed to the inside shoulder). One-lane incidents are assumed to occur in the outside lane. Two-or-more-lane incidents are assumed to occur in the outside two lanes. The incident is also assumed to occur on the intersection approach lanes as opposed to the departure lanes. This assumption is consistent with typical intersection crash patterns.

The scenario dataset generation procedure consists of a set of calculation steps. The calculations associated with each step are described in the following paragraphs.

Step 1: Acquire the Appropriate Dataset

During this step, the appropriate HCM dataset is acquired. This step proceeds day by day and analysis period by analysis period in chronological order. The date is used to determine whether a work zone or special event is present. If one is present, the appropriate alternative dataset is acquired. Otherwise, the base dataset is acquired. The hour-of-day, day-of-week, and month-of-year demand adjustment factors associated with each dataset are also acquired (as identified previously in the traffic demand variation procedure).

Step 2: Compute Weather Adjustment Factors

Signalized Intersections

The following equation is used to compute the saturation flow rate adjustment factor for analysis periods with poor weather conditions. It is used in Step 5 to estimate intersection saturation flow rate during weather events.

Equation 37-65

$$f_{rs,ap,d} = \frac{1.0}{1.0 + 0.48R_{r,ap,d} + 0.39R_{s,ap,d}}$$

where

$f_{rs,ap,d}$ = saturation flow adjustment factor for rainfall or snowfall during analysis period *ap* and day *d*,

$R_{r,ap,d}$ = rainfall rate during analysis period *ap* and day *d* (in./h), and

$R_{s,ap,d}$ = precipitation rate when snow is falling during analysis period *ap* and day *d* (in./h).

If Equation 37-65 is used for analysis periods with falling rain, the variable R_s should equal 0.0. If it is used for analysis periods with falling snow, the variable R_r should equal 0.0 and the variable R_s equals the precipitation rate (i.e., it is not a snowfall rate).

The factors obtained from Equation 37-65 apply when precipitation is falling. If the pavement is wet and there is no rainfall, the adjustment factor is 0.95. If there is snow or ice on the pavement and snow is not falling, the adjustment factor is 0.90.

Segments

The following equation is used to compute the free-flow speed adjustment factor for analysis periods with poor weather conditions. It is used in Step 7 to estimate the additional running time during weather events.

$$f_{s,rs,ap,d} = \frac{1.0}{1.0 + 0.48R_{r,ap,d} + 1.4R_{s,ap,d}}$$

Equation 37-66

where

$f_{s,rs,ap,d}$ = free-flow speed adjustment factor for rainfall or snowfall during analysis period *ap* and day *d*,

$R_{r,ap,d}$ = rainfall rate during analysis period *ap* and day *d* (in./h), and

$R_{s,ap,d}$ = precipitation rate when snow is falling during analysis period *ap* and day *d* (in./h).

If Equation 37-66 is used for analysis periods with falling rain, the variable R_s should equal 0.0. If it is used for analysis periods with falling snow, the variable R_r should equal 0.0 and the variable R_s equals the precipitation rate (i.e., it is not a snowfall rate).

The factors obtained from Equation 37-66 apply when precipitation is falling. If the pavement is wet and there is no rainfall, the adjustment factor is 0.95. If there is snow or ice on the pavement and snow is not falling, the adjustment factor is 0.90.

Step 3: Acquire Demand Adjustment Factors

During this step, the hour-of-day, day-of-week, and month-of-year demand adjustment factors associated with each analysis period are acquired (as identified previously in the traffic demand variation procedure). They are used in Step 6 to estimate the analysis period volumes.

Step 4: Compute Incident Adjustment Factors for Intersections

The following equation is used to compute the saturation flow rate adjustment factor for analysis periods associated with an incident. It is used in Step 5 to estimate intersection saturation flow rate during incidents.

$$f_{ic,int(i),n,m,ap,d} = \left(1.0 - \frac{N_{ic,int(i),n,m,ap,d}}{N_{n,int(i),n,m}}\right)\left(1.0 - \frac{b_{ic,int(i),n,ap,d}}{\sum_{m \in L,T,R} N_{n,int(i),n,m}}\right) \geq 0.10$$

Equation 37-67

with

Equation 37-68

$$b_{ic,int(i),n,ap,d} = 0.58 I_{fi,int(i),n,ap,d} + 0.42 I_{pdo,int(i),n,ap,d} + 0.17 I_{\text{other},int(i),n,ap,d}$$

where

$f_{ic,int(i),n,m,ap,d}$ = saturation flow adjustment factor for incident presence for movement m ($m = L$: left, T: through, R: right) on leg associated with NEMA phase n (n = 2, 4, 6, 8) at intersection i during analysis period ap and day d;

$N_{n,int(i),n,m}$ = number of lanes serving movement m on leg associated with NEMA phase n at intersection i (ln);

$N_{ic,int(i),n,m,ap,d}$ = number of lanes serving movement m blocked by the incident on leg associated with NEMA phase n at intersection i during analysis period ap and day d (ln);

$b_{ic,int(i),n,ap,d}$ = calibration coefficient based on incident severity on leg associated with NEMA phase n at intersection i during analysis period ap and day d;

$I_{pdo,int(i),n,ap,d}$ = indicator variable for property-damage-only (PDO) crash on leg associated with NEMA phase n at intersection i during analysis period ap and day d (= 1.0 if PDO crash, 0.0 otherwise);

$I_{fi,int(i),n,ap,d}$ = indicator variable for fatal-or-injury crash on leg associated with NEMA phase n at intersection i during analysis period ap and day d (= 1.0 if fatal-or-injury crash, 0.0 otherwise); and

$I_{\text{other},int(i),n,ap,d}$ = indicator variable for noncrash incident on leg associated with NEMA phase n at intersection i during analysis period ap and day d (= 1.0 if noncrash incident, 0.0 otherwise).

Equation 37-67 is applied to each approach traffic movement. For a given movement, the first term of Equation 37-67 adjusts the saturation flow rate on the basis of the number of lanes that are blocked by the incident. If the incident is located on the shoulder or in the lanes associated with another movement m (i.e., $N_{ic} = 0$), this term equals 1.0.

Equation 37-67 is used for each movement to estimate the saturation flow rate adjustment factor for incidents. If all lanes associated with a movement are closed because of the incident, an adjustment factor of 0.10 is used. This approach effectively closes the lane but does not remove it from the intersection, as described in the dataset.

Step 5: Compute Saturation Flow Rate for Intersections

During this step, the saturation flow rate for each intersection movement is adjusted by using the factors computed in Steps 2 and 4. The weather adjustment factor is applied to all movements at all intersections. The incident adjustment factor is applied only to the movements affected by an incident.

The weather and incident factors are multiplied by the saturation flow rate in the dataset to produce a revised estimate of the saturation flow rate.

Step 6: Compute Traffic Demand Volumes

Adjust Movement Volumes

During this step, the volume for each movement is adjusted by using the appropriate hour-of-day, day-of-week, and month-of-year factors to estimate the average hourly flow rate for the subject analysis period. The following equation is used for this purpose.

$$v_{int(i),j,h,d} = \frac{v_{\text{input},int(i),j}}{f_{hod,\text{input}} f_{dow,\text{input}} f_{moy,\text{input}}} f_{hod,h,d} d_{dow,d} f_{moy,d}$$

Equation 37-69

where

$v_{int(i),j,h,d}$ = adjusted hourly flow rate for movement j at intersection i during hour h and day d (veh/h),

$v_{\text{input},int(i),j}$ = movement j volume at intersection i (from HCM dataset) (veh/h),

$f_{hod,h,d}$ = hour-of-day adjustment factor based on hour h and day d,

$f_{dow,d}$ = day-of-week adjustment factor based on day d,

$f_{moy,d}$ = month-of-year adjustment factor based on day d,

$f_{hod,\text{input}}$ = hour-of-day adjustment factor for hour and day associated with v_{input},

$f_{dow,\text{input}}$ = day-of-week adjustment factor for day associated with v_{input}, and

$f_{moy,\text{input}}$ = month-of-year adjustment factor for day associated with v_{input}.

If a 15-min analysis period is used, the adjusted hourly flow rate is applied to all four analysis periods coincident with the subject hour h. Equation 37-69 is also used to adjust the volumes associated with each driveway on each segment.

Random Variation Among 15-min Periods

If a 15-min analysis period is used, the analyst has the option of adding a random element to the adjusted hourly volume for each movement and analysis period. Including this random variation provides a more realistic estimate of performance measure variability. However, it ensures that every analysis period is unique (thereby making it less likely that similar scenarios can be found for the purpose of reducing the total number of scenarios to be evaluated). If this option is applied, the turn movement volumes at each signalized intersection are adjusted by using a random variability based on the peak hour factor. Similarly, the turn movement volumes at each driveway are adjusted by using a random variability based on a Poisson distribution.

If the analyst wants to add a random element to the adjusted hourly volume, the first step is to use the following equation to estimate the demand flow rate variability adjustment factor.

$$f_{int(i),j,h,d} = \frac{1.0 - PHF_{int(i)}}{PHF_{int(i)}} \sqrt{0.25 v_{int(i),j,h,d}} \exp\left(-0.00679 + 0.004 PHF_{int(i)}^{-4}\right)$$

Equation 37-70

where

$f_{int(i),j,h,d}$ = adjustment factor used to estimate the standard deviation of demand flow rate for movement j at intersection i during hour h and day d,

$PHF_{int(i)}$ = peak hour factor for intersection i, and

$v_{int(i),j,h,d}$ = adjusted hourly flow rate for movement j at intersection i during hour h and day d (veh/h).

The second step is to use the following equation to compute the randomized hourly flow rate for each movement at each signalized intersection.

Equation 37-71

$$v^*_{int(i),j,ap,d} = 4.0 \times gamma^{-1}\begin{pmatrix} p = Rf_{ap,d}, \\ \mu = 0.25 v_{int(i),j,h,d}, \\ \sigma = f_{int(i),j,h,d}\sqrt{0.25 v_{int(i),j,h,d}} \end{pmatrix}$$

where

$v^*_{int(i),j,ap,d}$ = randomized hourly flow rate for movement j at intersection i during analysis period ap and day d (veh/h),

$gamma^{-1}(p, \mu, \sigma)$= value associated with probability p for cumulative gamma distribution with mean μ and standard deviation σ,

$Rf_{ap,d}$ = random number for flow rate for analysis period ap and day d,

$v_{int(i),j,h,d}$ = adjusted hourly flow rate for movement j at intersection i during hour h and day d (veh/h), and

$f_{int(i),j,h,d}$ = adjustment factor used to estimate the standard deviation of demand flow rate for movement j at intersection i during hour h and day d.

Similarly, the following equations are used to compute the randomized hourly flow rates for each driveway. The first equation is used if the adjusted hourly flow rate is 64 veh/h or less. The second equation is used if the flow rate exceeds 64 veh/h.

If $v_{int(i),j,h,d} \leq 64$ veh/h, then

Equation 37-72

$$v^*_{int(i),j,ap,d} = 4.0 \times Poisson^{-1}\left(p = Rf_{ap,d},\ \mu = 0.25 v_{int(i),j,h,d}\right)$$

If otherwise, then

Equation 37-73

$$v^*_{int(i),j,ap,d} = 4.0 \times normal^{-1}\begin{pmatrix} p = Rf_{ap,d}, \\ \mu = 0.25 v_{int(i),j,h,d}, \\ \sigma = \sqrt{0.25 v_{int(i),j,h,d}} \end{pmatrix}$$

where

$v^*_{int(i), j, ap, d}$ = randomized hourly flow rate for movement j at intersection i during analysis period ap and day d (veh/h),

$Poisson^{-1}(p, \mu)$ = value associated with probability p for the cumulative Poisson distribution with mean μ,

$Rf_{ap,d}$ = random number for flow rate for analysis period *ap* and day *d*,

$v_{int(i),j,h,d}$ = adjusted hourly flow rate for movement *j* at intersection *i* during hour *h* and day *d* (veh/h), and

$normal^{-1}(p, \mu, \sigma)$ = value associated with probability *p* for a cumulative normal distribution with mean μ and standard deviation σ.

Step 7: Compute Speed for Segments

Additional Delay

During this step, the effect of incidents and weather on segment speed is determined. This effect is appended to the HCM dataset as an additional delay incurred along the segment. The variable d_{other} in Equation 17-6 is used with this approach. The additional delay is computed with the following equations.

$$d_{\text{other},seg(i),n,ap,d} = L_{seg(i)} \left(\frac{1.0}{S^*_{fo,seg(i),n,ap,d}} - \frac{1.0}{S_{fo,seg(i),n}} \right)$$

Equation 37-74

with

$$S^*_{fo,seg(i),n,ap,d} = S_{fo,seg(i),n} \times f_{s,rs,sp,d} \times \left(1.0 - \frac{b_{ic,seg(i),n,ap,d}}{N_{o,seg(i),n}} \right)$$

Equation 37-75

$$b_{ic,seg(i),n,ap,d} = 0.58 I_{fi,seg(i),n,ap,d} + 0.42 I_{pdo,seg(i),n,ap,d} + 0.17 I_{\text{other},seg(i),n,ap,d}$$

Equation 37-76

where

$d_{\text{other},seg(i),n,ap,d}$ = additional delay for the direction of travel served by NEMA phase *n* (*n* = 2, 6) on segment *i* during analysis period *ap* and day *d* (s/veh);

$L_{seg(i)}$ = length of segment *i* (ft);

$S_{fo,seg(i),n}$ = base free-flow speed for the direction of travel served by NEMA phase *n* on segment *i* (ft/s);

$S^*_{fo,seg(i),n,ap,d}$ = adjusted base free-flow speed for the direction of travel served by NEMA phase *n* on segment *i* during analysis period *ap* and day *d* (ft/s);

$f_{s,rs,ap,d}$ = free-flow speed adjustment factor for rainfall or snowfall during analysis period *ap* and day *d*;

$b_{ic,seg(i),n,ap,d}$ = calibration coefficient based on incident severity on leg associated with NEMA phase *n* at intersection *i* during analysis period *ap* and day *d*;

$N_{o,seg(i),n}$ = number of lanes serving direction of travel served by NEMA phase *n* on segment *i* (ln);

$I_{pdo,seg(i),n,ap,d}$ = indicator variable for property-damage-only (PDO) crash in the direction of travel served by NEMA phase *n* on segment *i* during analysis period *ap* and day *d* (= 1.0 if PDO crash, 0.0 otherwise);

$I_{fi,seg(i),n,ap,d}$ = indicator variable for fatal-or-injury crash in the direction of travel served by NEMA phase n on segment i during analysis period ap and day d (= 1.0 if fatal-or-injury crash, 0.0 otherwise); and

$I_{\text{other},seg(i),n,ap,d}$ = indicator variable for noncrash incident in the direction of travel served by NEMA phase n on segment i during analysis period ap and day d (= 1.0 if noncrash incident, 0.0 otherwise).

The delay estimated from Equation 37-74 is added to the "other delay" variable in the dataset to produce a combined "other delay" value for segment running speed estimation.

Segment Lane Closure

If an incident is determined to be located in one or more lanes, the variable for the number of through lanes on the segment is reduced accordingly. This adjustment is made for the specific segment and direction of travel associated with the incident.

The variable indicating the number of major-street through lanes at each driveway is reduced in a similar manner when the incident occurs on a segment and closes one or more lanes. This adjustment is made for each driveway on the segment affected by the incident.

Step 8: Adjust Critical Left-Turn Headway

Research indicates that the critical headway for left-turn drivers increases by 0.7 to 1.2 s, depending on the type of weather event and the opposing lane associated with the conflicting vehicle. The recommended increase in the critical headway value for each weather condition is given in Exhibit 37-23.

Exhibit 37-23
Additional Critical Left-Turn Headway due to Weather

Weather Condition	Additional Critical Left-Turn Headway (s)
Clear, snow on pavement	0.9
Clear, ice on pavement	0.9
Clear, water on pavement	0.7
Snowing	1.2
Raining	0.7

Step 9: Save Scenario Dataset

During this step, the dataset with the updated values is saved for evaluation in the next stage of the reliability methodology. One dataset is saved for each analysis period (i.e., scenario).

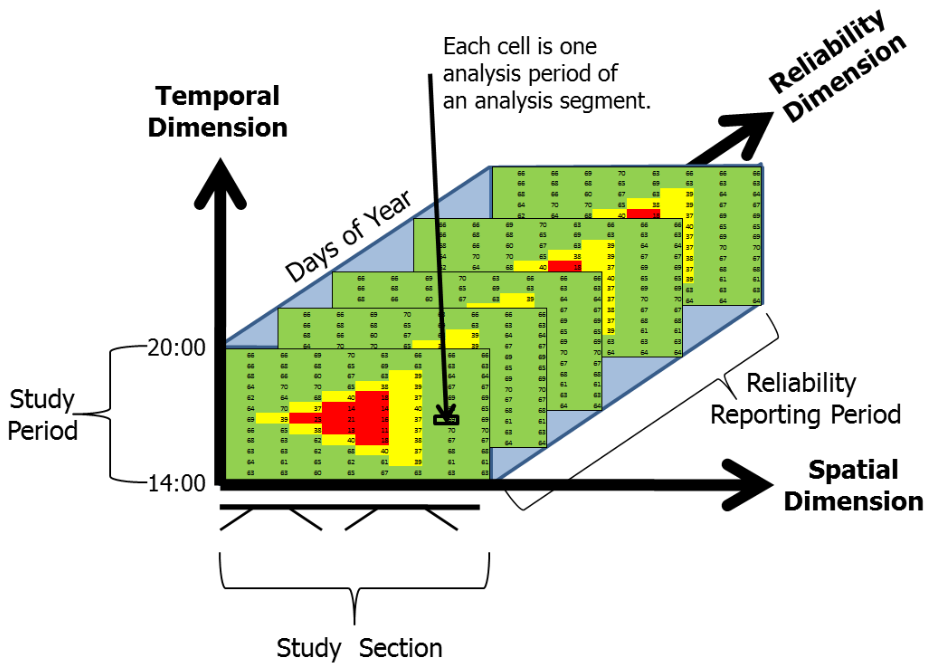
5. MEASURING RELIABILITY IN THE FIELD

This section provides a recommended method for measuring reliability in the field. The intent is to provide a standardized method for gathering and reporting travel time reliability for freeways and arterials directly from field sensors, which can be used for validating estimates of reliability produced by the HCM method and for consistently comparing reliability across facilities.

MEASUREMENT OF TRAVEL TIME RELIABILITY

Every current method of measuring travel time reliability in the field involves some form of sampling of the three-dimensional reliability box. The three dimensions of reliability are the study section of the facility, the daily study period, and the reliability reporting period (Exhibit 37-24). For example, the travel time reliability may be computed for a 1-mi length of freeway during the morning peak hour for all nonholiday weekdays in a year.

Exhibit 37-24
Three-Dimensional Reliability Box



DATA SOURCES OF TRAVEL TIME RELIABILITY

Travel time reliability may be measured by recording a sample of the vehicle travel times over a fixed length of facility (probe vehicle method) or by recording the spot speeds of all vehicles as they pass over a set of stationary detectors. The latter method will be called for convenience the "loop detector method," although many technologies are available (radar, video, etc.) in addition to inductive loop detectors for measuring spot speeds.

Loop Detectors and Similar Point Measures of Speed

Loop sensors (or similar point measures of speed) can be as close as ⅓ to ½ mi apart, but they can be much farther apart.

Single loops will measure the time a vehicle spends within the typical 12-ft detection range of the loop and will divide this time by the estimated average vehicle length (supplied by the operator) to arrive at the estimated speed of the vehicle.

Double loops will measure the lag between the time the leading edge of the vehicle arrives at the first loop and the time the leading edge arrives at the second loop. The distance between the two loops is divided by the time difference between the arrival of the leading edge of the vehicle at the upstream loop and its arrival at the downstream loop to obtain the vehicle speed for the short distance between the two loops.

These spot speeds (whether measured with single or dual loops) are often aggregated into average vehicle speeds for 5-min analysis periods.

For study sections where multiple loop detector stations are present, the speeds from the detectors may be simply averaged or may be length weighted averaged (where each detector is assumed to represent a different length of the facility). The study period used to compute the average may be offset by the average travel time of vehicles as they move from one segment to the next.

Probe Vehicles

Electronic toll tag or Bluetooth readers can be deployed at certain segments of freeway so that time stamps of vehicles crossing at these locations can be tracked. When a vehicle with a toll tag or a discoverable Bluetooth device crosses locations with readers, identification of the same vehicle can be matched with different time stamps and corresponding locations. Then the travel time between a pair of toll tag reader locations can be obtained.

A filtering algorithm that removes vehicles from the sample that take an excessive amount of time to appear at the downstream detector is required to remove vehicles that leave the facility to stop for errands between the two detectors. The closer together the two readers, the tighter the filtering criterion can be.

Unreasonably high travel times obtained from toll tag readers should be discarded by setting a cutoff point at the 99th percentile of the raw data. If, after filtering, the data still show a mean travel time greater than the 95th percentile travel time (an indication that some vehicles stopping for errands are still in the dataset), the highest travel time point should be removed, and the removal process should be repeated until the mean travel time falls below the 95th percentile travel time.

Comparison of Sampling Methods

Loop detectors take a vertical sample of the facility time–space diagram, while probe vehicle (e.g., electronic toll collection) detectors take a diagonal sample of the facility time–space diagram (compare Exhibit 37-25 and Exhibit 37-26).

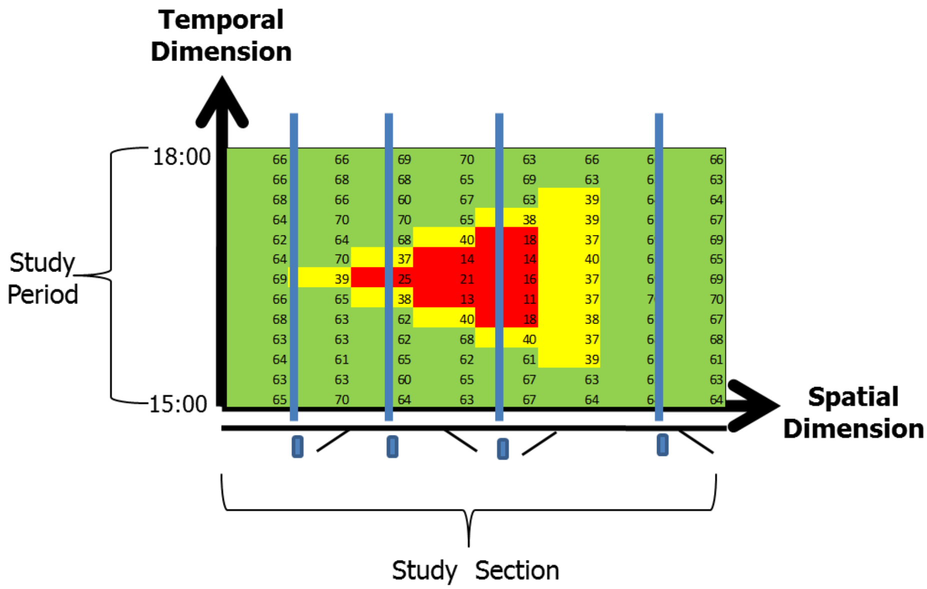


Exhibit 37-25
Spot Speed (Vertical) Sampling of Loop Detectors

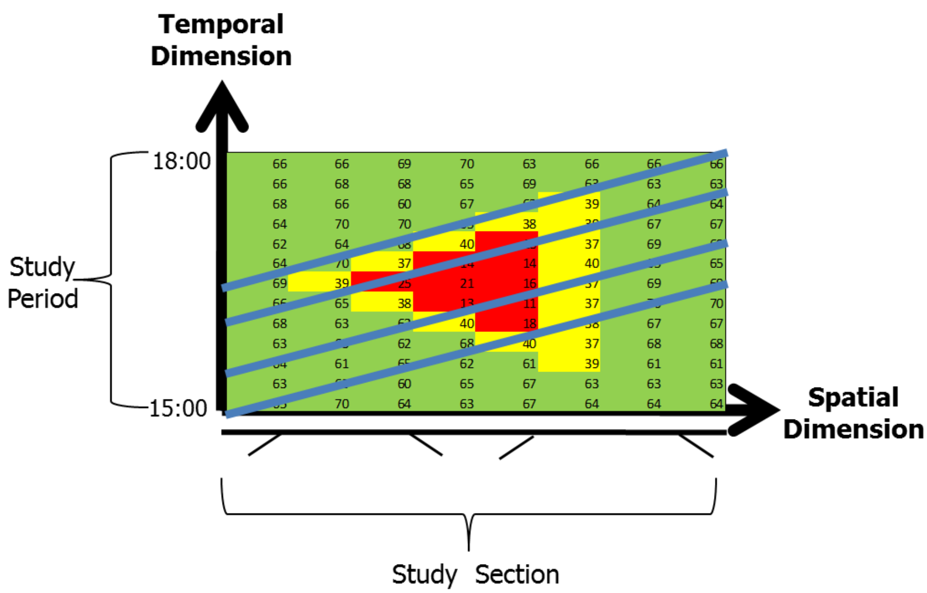
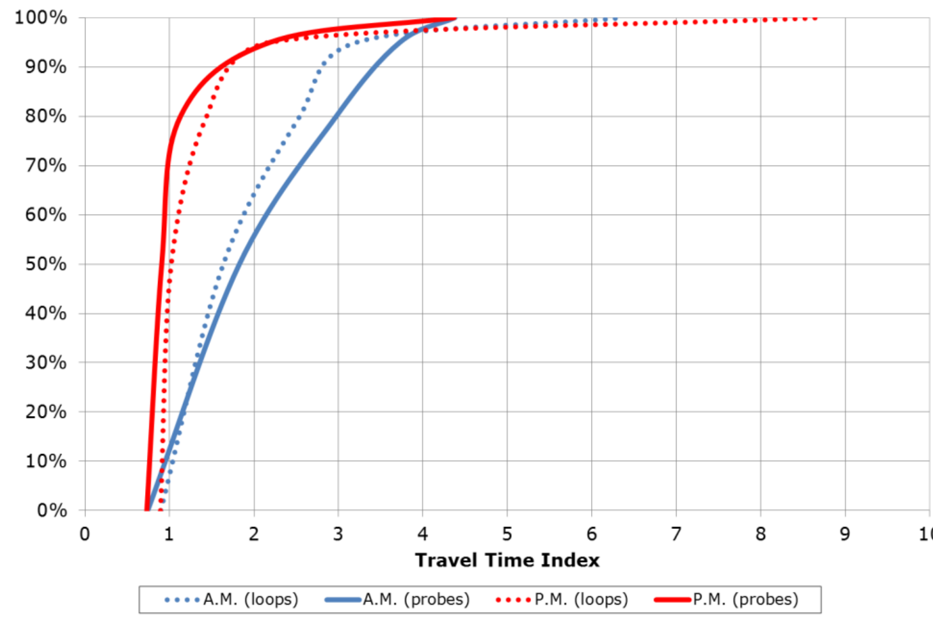


Exhibit 37-26
Time–Space (Diagonal) Sampling of Probe Vehicle Detectors

Since the two measurement methods sample the three-dimensional reliability space differently, they will produce slightly different estimates of the travel time reliability distribution, as illustrated for one freeway in Exhibit 37-27. However, the differences between the methods will generally be less than the differences in reliability between different peak periods.

Exhibit 37-27
Comparison of Loop Detector and Probe Cumulative Travel Time Distributions



Source: Kittelson & Associates, Inc.
Note: I-80 westbound, Contra Costa County, California.

Each method has its strengths and weaknesses, and neither method is always the best. A dense network of loop detectors may produce better estimates than a sparse network of toll tag readers. The reverse may also be true. Thus the choice of method is contingent on the density of the detection available for each method.

RECOMMENDED METHOD FOR COMPUTING RELIABILITY BY USING LOOP DETECTORS

The recommended method for computing travel time reliability statistics for freeways by using loop detectors or other stationary sensors of spot speeds is described below. Because of the highly varying nature of speeds by distance from signal on urban streets, the loop detector method is *not* recommended for urban streets.

1. *Define reliability study bounds.* Select facility direction, length, study period, and reliability reporting period. The recommended reliability reporting period should be at least 150 days and preferably closer to 250 days.
2. *Download data.* Download lane-by-lane vehicle speeds and volumes aggregated or averaged to 5-min periods for all mainline speed detectors for the selected study direction, within the selected facility length and study period, and for all days included in the reliability reporting period.
3. *Quality check data.*
    a. If the system estimates data to fill in for gaps in detector data (detectors down), remove all data with less than 70% observed rating.
    b. Remove unrealistic speeds from the dataset. (Use local knowledge to determine what is unreasonable. In the absence of local knowledge, use these two criteria to remove data: average speeds greater than

120% of the posted speed limit; average speeds observed for fewer than 5 veh.)

c. Gaps in data are treated as nonobservations.

4. *Compute 5-min VMTs.*

   a. For each detector station, identify the length of facility represented by the detector. This is usually half the distance to the upstream detector station plus half the distance to the downstream detector, but it can be a different value based on local knowledge of the facility.

   b. Sum up volumes across all lanes at the detector station for 5-min time periods.

   c. Neglect periods when the detector is not functioning.

   d. $VMT(t, d) = V(t, d) \times L(d)$, where $VMT(t, d)$ = vehicle miles traveled during time period t measured at detector station d, $L(d)$ = length represented by detector station d (mi), and $V(t, d)$ = sum of lane volumes (veh) measured at detector station d during time period t.

5. *Compute 5-min vehicle hours traveled.*

   a. $VHT(t, d) = VMT(t, d) / S(t, d)$, where $VHT(t, d)$ = vehicle hours traveled during time period t measured at lane detector station d and $S(t, d)$ = arithmetic average speed of vehicles (mi/h) measured during time period t at lane detector station d.

   b. Neglect periods when the detector is not functioning.

6. *Compute free-flow speed for facility.*

   a. Select a nonholiday weekend.

   b. For each detector, obtain 5-min speeds for 7 to 9 a.m. on a typical weekend morning.

   c. Neglect periods when the detector is not functioning.

   d. Quality control for excessively high speeds or excessively low volumes as explained earlier.

   e. Identify the 85th percentile highest speed. That is the free-flow speed for the detector.

   f. Convert speed to segment travel times.

   g. Sum segment times to obtain facility free-flow travel times.

7. *Compute TTIs for time periods.* The TTI for each 5-min period at each detector is computed as follows:

$$TTI(t,d) = \frac{\sum_d VHT(t,d)}{\sum_d VHTFF(t,d)}$$

where $VHT(t, d)$ is vehicle hours traveled for prevailing speeds during time t at detector d and $VHTFF(t, d)$ is vehicle hours traveled at theoretical free-flow speeds for detector d during time t.

8. *Compute mean TTI for facility.*

$$TTI_{\text{mean}} = \frac{\sum_{t,d} VHT(t,d)}{\sum_{t,d} VHTFF(t,d)}$$

9. *Compute PTI for facility.* The PTI is the 95th percentile TTI from the set of TTIs calculated in Step 7.

RECOMMENDED METHOD FOR COMPUTING RELIABILITY BY USING PROBE VEHICLES

The recommended method for computing travel time reliability statistics for freeways and arterials by using probe vehicles and Bluetooth, toll tag, or license plate readers is described below. The instructions assume that the data are obtained from a commercial vendor of historical TMC segment speed data.

1. *Define reliability study bounds*. Select the facility direction, length, study period, and reliability reporting period. The recommended reliability reporting period should be at least 150 days and preferably closer to 250 days.
2. *Download data.* Download TMC segment speeds (or travel times if Bluetooth or toll tag reader data are being used) aggregated or averaged to 5-min (or similar) periods for all mainline segments for the selected study direction and selected facility length, for all study periods and days included in the reliability reporting period.
3. *Quality check data.*
   a. Remove travel times that fall in the top 99th percentile of the data. This removes trips that stop or leave the facility for errands and then return.
   b. If travel time data (e.g., Bluetooth or toll tag reader data) are being used, convert data to speeds for error-checking purposes.
   c. Remove unrealistic speeds from the dataset. (Use local knowledge to determine what is unreasonable. In the absence of local knowledge, remove data with average speeds greater than 120% of the posted speed limit.)
4. *Compute facility travel times for each analysis period.*
   a. For each TMC (or Bluetooth or toll tag reader) segment, identify its length in miles (to the nearest 0.01 mi).
   b. Divide the segment length by speed to obtain the segment travel time for each analysis period (skip this step if Bluetooth or toll tag travel time data are being used).
   c. Sum the segment travel times to obtain the facility travel time for each time period.
5. *Compute free-flow speed for facility.*
   a. If the segment reference speed provided by the commercial vendor is reliable, that can be used for the free-flow speed. If it is not reliable, perform the following steps.

b. Select a nonholiday weekend.

c. For each segment, obtain speeds for 5-min time periods for 7 to 9 a.m. on a typical weekend morning.

d. Quality control for excessively high speeds or travel times as explained earlier.

e. Identify the 85th percentile highest speed. That is the free-flow speed for the segment.

f. Convert the segment speed to segment travel times (segment length divided by segment speed).

g. Sum the segment times to obtain facility free-flow travel times.

6. *Compute TTIs for time periods.* The TTI for each 5-min time period is the ratio of the mean facility travel time for the 5-min period to the free-flow travel time. It is computed as follows:

$$TTI(t) = \frac{\sum_d VHT(t,d)}{\sum_d VMT(t,d)}$$

7. *Compute mean TTI for facility.*

$$TTI_{\text{mean}} = \frac{\sum_{t,d} VHT(t,d)}{\sum_{t,d} VMT(t,d)}$$

8. *Compute PTI for facility.* The PTI is the 95th percentile TTI from the set of TTIs calculated in Step 6.

6. EXAMPLE PROBLEM

Example Problems 1–7 are located in Chapter 36.

EXAMPLE PROBLEM 8: EXISTING FREEWAY RELIABILITY

Objective

This example problem illustrates the following process:

1. Calculating reliability statistics for a freeway facility by using the minimum required data for the analysis,
2. Identifying key reliability problems on the facility, and
3. Diagnosing the causes (e.g., demand, weather, incidents) of reliability problems on the facility.

Site

The study freeway facility is a 12.5-mi portion of eastbound I-40 between Durham and Raleigh, North Carolina, bounded by NC-55 to the west and NC-54 to the east (Exhibit 37-28). The eastbound direction is most heavily utilized by commuters on weekdays, with a peak hour of 5 to 6 p.m. The posted speed limit is 65 mi/h. A weaving section near the downstream end of the facility creates a recurring bottleneck during peak demand levels.

Exhibit 37-28
Example Problem 8: Study Freeway Facility

Source: ©2012 Google.

Minimum Required Data Inputs

The data listed below are required to perform a reliability analysis of a freeway facility. Additional desirable data are also identified, but this example problem assumes that the additional desirable data are not available. Instead, this example illustrates the use of defaults and lookup tables to substitute for the desirable data.

- Data required for an HCM freeway facility analysis (Chapter 10):
    - Facility volumes by 15-min analysis periods (time slices) for a single day's peak period.
    - Facility geometry and controls by analysis segment and by analysis period (if controls vary by analysis period) for the study period (if controls or geometry vary by time of day, day of week, or month of year).
    - *Desirable: single day's peak period facility travel times for calibrating a traditional HCM 2010 operations analysis model for the facility.*
- Data required for estimating demand variability:
    - AADT, directional factor (D), and peak period demand profiles (K-factors).
    - *Desirable: archived peak period mainline volume counts for previous year.*
- Data required for estimating incident frequencies:
    - Collision reports for the prior 3-year period.
    - *Desirable: detailed incident logs including frequency, duration, and location of incidents for a similar period.*
- Data required for estimating weather frequencies:
    - Weather reports for at least the prior 3-year period.
    - *Desirable: 10-year weather data from a nearby weather station.*
- Optional extra data for calibrating estimates:
    - Facility travel times (or spot speeds) and volumes by 15-min analysis periods (time slices) for the target study period (peak periods, days of weeks, months of year, etc.).

Computational Steps

This example problem proceeds through the following steps:

1. Scoping the bounds of the reliability analysis:
    a. Establishing the analysis purpose, scope, and approach;
    b. Selecting an appropriate study period;
    c. Selecting an appropriate reliability reporting period; and
    d. Selecting appropriate reliability performance measures and thresholds of acceptable performance.
2. Coding the HCM facility operations analysis:
    a. Identifying the sources of unreliability to be analyzed;
    b. Coding base conditions; and
    c. Coding alternative datasets, if any.
3. Estimating the demand variability profile.
4. Estimating severe weather frequencies.
5. Estimating incident frequencies.

6. Generating scenarios and the probabilities of their occurrence.
7. Applying the Chapter 10 freeway facility method.
8. Performing quality control, error checking, and validation.
9. Calculating performance measures.
10. Diagnosing the causes of unreliable performance.
11. Interpreting results.

Step 1: Scope the Bounds of the Reliability Analysis

While most professional engineers and planners are already well trained in scoping a traditional highway capacity analysis, travel time reliability introduces some extra considerations not part of a traditional capacity analysis:

- Selecting an appropriate *study period* for reliability (hours of day) and an appropriate *reliability reporting period* (days of week, months of year),
- Selecting appropriate reliability performance measures according to the agency's reliability objectives and the facility type, and
- Selecting thresholds of acceptable performance.

A reliability analysis has much greater data and computational demands than a traditional HCM operations analysis. Therefore, it should be tightly scoped to ensure that the analyst has the resources to complete the analysis. Furthermore, a loosely scoped analysis that provides more days and hours than needed runs the risk of "washing out" the reliability results by mixing too many hours or days of free-flow conditions into the analysis.

Purpose

To focus the analysis, the purpose for performing it should be identified. In this example, the reliability analysis of existing conditions is being performed for the following purposes:

- To determine whether the facility is experiencing significant reliability problems, and
- To diagnose the primary causes of the reliability problems on the facility so that an improvement program can be developed.

Determining the Reliability Analysis Box

The reliability reporting period has three dimensions: (*a*) the geometric limits of the facility to be evaluated (the *study section*), (*b*) the period(s) within the day when the analysis is to be performed (the *study period*), and (*c*) the days of the year over which reliability is to be computed and reported (the *reliability reporting period*). The result is a spatial–temporal reliability box (see Exhibit 37-24) within which reliability is computed.

The reliability box should be dimensioned so that it includes all of the recurring congestion (congestion arising under recurring demand conditions, in fair weather, without incidents) of interest for the analysis. This favors a large reliability box. However, the larger the reliability box, the greater the number of instances of free-flow conditions, which will tend to mask or wash out the reliability problems.

In this example, an examination of the facility over several days has determined the general spatial and temporal boundaries of congestion on the facility under fair weather, nonincident conditions. The selected study period was the 6-h-long weekday afternoon peak period (2 to 8 p.m.), and the study section was the 12.5-mi facility length between NC-55 and NC-54 (corresponding to 34 HCM analysis segments). All of the instances where speeds regularly drop below 40 mi/h are encompassed within the study section and study period. Exhibit 37-29 shows an example of the speed profile when an incident occurs in the farthest downstream segment on the facility.

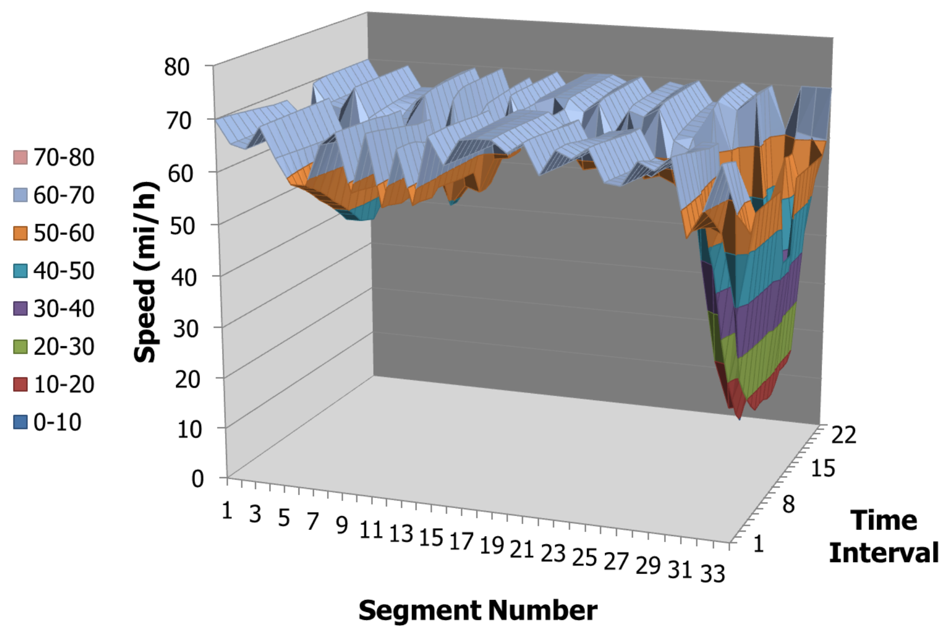


Exhibit 37-29
Example Problem 8: Sample Congested Speed Profile on I-40

Once the study section length and the study period have been selected, the next step is to determine how many (and which) days of the year to compute the reliability for (the reliability reporting period). The objective of setting the reliability reporting period is to focus the analysis on days when reliability is a concern. The reporting period should include enough days so that the probability of encountering a significant number and range of incident types is high. A minimum of 100 days is recommended for the reporting period, although a full-year analysis is preferred.

Thus, for this example, weekdays for a full year were selected for the reliability reporting period. At 5 weekdays per week, 52 weeks plus one day per year, there are 261 weekdays per year (including holidays). Holidays may be excluded from the reliability reporting period if they result in lower-than-normal p.m. peak period demands. (In this case, holidays were not deemed to be a significant factor affecting reliability and were therefore included in the reliability analysis.)

If an agency wishes to focus on nonweather effects and avoid vacation effects, a single season may be selected rather than a full year. The selection of the appropriate reliability reporting period hinges on the agency's purpose for the analysis.

Selecting Reliability Performance Measures

For instructional purposes, all of the reliability performance measures shown in Exhibit 37-30 will be computed. However, for a typical application, computation of one or two performance measures most useful to the agency's analysis purpose is recommended.

Exhibit 37-30
Example Problem 8: Reliability Performance Measures to Be Evaluated

Measure	Definition
TTI_{mean}	Mean travel time divided by free-flow travel time
PTI	95th percentile travel time divided by free-flow travel time
TTI_{80}	80th percentile travel time divided by free-flow travel time
Semi–standard deviation	One-sided standard deviation, referenced to free-flow
Failure/on-time	Percent of trips less than 40 mi/h
Standard deviation	Usual statistical definition
Misery index	Average of top 5% of travel times divided by free-flow travel time
Reliability rating	Percentage of VMT at a TTI less than 1.33

Since all performance measures are derived from the same travel time distribution (see Exhibit 36-5 in Chapter 36), once an agency has picked one or two measures for the reliability analysis, additional measures do not bring significant new information to the results. In that sense, it is most important that the agency select performance measures consistently across different reliability analyses, allowing agency staff and stakeholders to begin developing an understanding of these metrics.

In this example, the agency could pick TTI_{mean} so that average performance could be evaluated (the mean is useful for computing total benefits later). As an indicator of reliability, the agency could pick TTI_{80} or PTI.

Selecting Thresholds of Acceptable Performance

Ideally, an agency has already developed its own thresholds of acceptable reliability performance on the basis of locally collected data. However, in this case, the agency responsible for the freeway has not yet assembled sufficient data on the reliability of its own facilities to have confidence in setting its own standards. Consequently, two standards of performance will be evaluated in this example problem as part of the reliability assessment.

The first standard will be determined by comparing performance of the I-40 facility with that of other facilities in the SHRP 2 L08 dataset. The agency uses the values in Exhibit 37-1 to select acceptable TTI_{mean} and PTI values as its desired reliability performance thresholds. For example, the operating agency may select greater reliability than the worst 10% of U.S. urban freeway facilities in the SHRP 2 L08 dataset as a performance threshold. Thus, if the TTI_{mean} for the facility is computed to be greater than 1.78, the facility's reliability will be considered unacceptable. Similarly, a computed PTI exceeding 3.34 will be considered unacceptable.

The setting of the second standard is based on the agency's congestion management goal of operating its freeways at 40 mi/h or better during the majority of the peak periods within the year. This standard requires computation of a modified travel time performance index, called the *policy index* (PI), that uses the agency's 40-mi/h target speed in place of the free-flow speed.

$$\mathrm{PI} = \frac{\text{mean travel time}}{\text{travel time at 40 mi/h}}$$

Since the agency's goal is for the mean annual peak period speed on the facility to be 40 mi/h or higher, if the PI exceeds 1.00, the reliability of the facility will be considered unacceptable.

Step 2: Code the HCM Facility Operations Analysis

Selecting Reliability Factors for Evaluation

The major causes of travel time reliability problems are demand surges, weather, incidents, special events, and work zones. Evaluating all possible causes of reliability problems puts a significant strain on analytical resources, so it is recommended that rarer causes of unreliability be excluded from the reliability analysis. In addition, the purpose of the analysis may suggest that some causes can be bundled together.

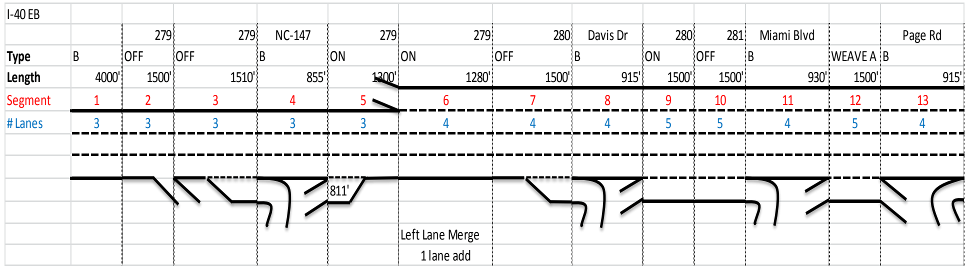
The study facility in this case is large, and adjacent special events do not significantly affect operations during the selected study period (most events are on weekends). Consequently, the effects of special events do not need to be evaluated separately and can be bundled in with other causes of surges in demand. Similarly, operation of work zones is not planned during weekday peak periods on the facility in the analysis year, so work zones can be excluded from the reliability analysis.

Coding Base Conditions

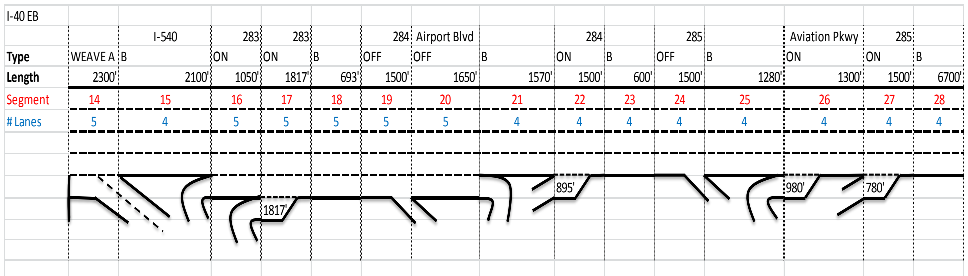
The base HCM analysis input file (the seed file) was coded for the selected study section and study period by using the procedures and guidance contained in Chapters 10 through 13. Demands, geometries, and free-flow speed were obtained for a single, typical, fair-weather, nonincident, nonholiday, weekday p.m. peak period (2 to 8 p.m.). Exhibit 37-31 shows the geometry of the study section of the facility. Exhibit 37-32 shows a portion of the input entries for the seed file.

Mainline volumes were obtained from side-fire radar stations spaced roughly 1.5 mi apart. Ramp volumes were counted for 2 weeks by using portable tube counters. A typical fair-weather weekday when daily traffic was close to the annual average daily traffic was selected from the 2-week count period. Default values of 5% trucks, 0% recreational vehicles, and 0% buses were used to account for heavy vehicles.

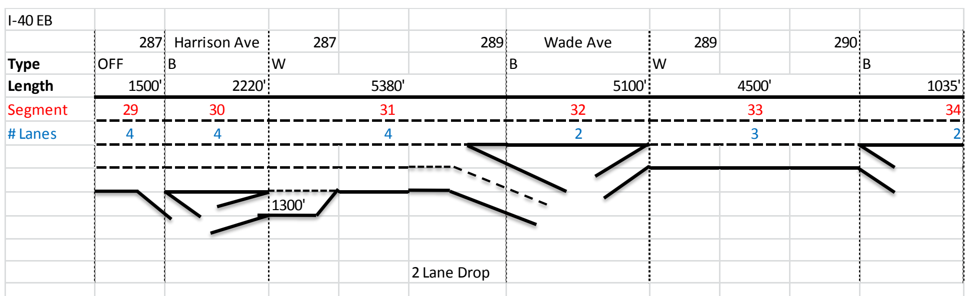
Exhibit 37-31
Example Problem 8: Study Section Geometry



Section A



Section B



Section C

There were no extended grades in excess of 2% for longer than 0.5 mi on the facility (see page 11-15), and the facility has a general level vertical profile, so a general terrain category of "level" was used to characterize the vertical geometry of the facility.

Segment lengths and number of lanes were obtained by field inspection or Google aerial photos. Lane widths are a standard 12 ft. The free-flow speed was estimated with Equation 11-1.

Release Date:	Release February 2013							
Project Name:	I-40 EB							
SEGMENT NUMBER :	1	2	3	4	5	6	7	8
SECTION NUMBER :	1	2	3	4	5	6	7	8
SEGMENT LABEL :	S01	S02	S03	S04	S05	S06	S07	S08
Type (B, ONR, OFR, R, or W)	B	OFR	OFR	B	ONR	ONR	R	OFR
Length (ft)	4000	1500	1500	855	1300	1280	220	1280
Number of Lanes	3	3	3	3	3	3	4	4
FF Speed (Mi/hr)	70	70	70	70	70	70	70	70
Segment Demand (vph)	3,427	3,427	3,359	3,017	3,396	4,889	4,889	4,889
Capacity Adjustment Factor	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Origin Demand Adjustment Factor	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Destination Demand Adjustment Factor	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Speed Adjustment Factor	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
% Trucks	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
% RV's	0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
On-Ramp Demand (vph)					379	1,493		
On-Ramp % Trucks					5	5		
On-Ramp % RV's					0	0		
Off-Ramp Demand(vph)		68	342					190
Off-Ramp % Trucks		5	5					5
Off-Ramp % RV's		0	0					0
Acc/ Dec Lane Length (ft)		300	300		800	1280		300
Number of Lanes on Ramp		1	1		1	1		1
Ramp on Left or Right (L / R)		Right	Right		Right	Left		Right
Ramp FFS (mi/hr)		45	45		45	55		45
Ramp Metering Rate (vph)					2100	2100		

Exhibit 37-32
Example Problem 8: Sample Freeway Input Entries for Seed File

Coding Alternative Datasets

Since there is no need to account for special events or work zones, no alternative datasets need to be created. If there had been a need for them, they would have been developed in the same way as the base dataset, with appropriate modifications to the input data to reflect changes in demand, geometry, and traffic control.

Step 3: Estimate the Demand Variability Profile

The total number of scenarios that must be evaluated significantly affects the processing time and the time required for analysis of the results. The number of scenarios is the product of the number of demand levels, weather levels, and incident levels selected for evaluation. Thus, any reduction in the number of demand, weather, and incident levels needed for the reliability analysis will result in significant processing and evaluation time savings for the analysis.

On the basis of examination of local data on I-40 demand variability over the course of a year (Exhibit 37-33), it was determined that weekday demand variability over the year at the site could be adequately represented by three demand patterns (Monday–Wednesday, Thursday, Friday) and four month types grouped by the major seasons of the year (December–February, March–May, June–August, September–November). Thus, 60 potential demand levels (5 weekdays × 12 months) could be consolidated into 12 demand levels (3 weekday patterns × 4 month types). Days and months with similar ratios of monthly ADT to AADT for a given demand pattern were grouped together. All entries were normalized to a Monday in January. In the event that such detailed data are unavailable, the user can refer to the national urban or rural default demand ratios provided in Exhibits 36-22 and 36-23, respectively, in Chapter 36.

Exhibit 37-33
Example Problem 8: Demand Ratios for I-40 Case Study (ADT/Mondays in January)

	Day of Week				
Month	**Monday**	**Tuesday**	**Wednesday**	**Thursday**	**Friday**
January	1.00	1.03	1.04	1.05	1.08
February	0.94	1.01	1.04	1.09	1.14
March	1.04	1.07	1.06	1.11	1.17
April	1.07	1.09	1.10	1.16	1.22
May	1.08	1.11	1.11	1.16	1.21
June	1.08	1.09	1.07	1.14	1.18
July	1.08	1.07	1.10	1.15	1.18
August	1.05	1.05	1.06	1.09	1.16
September	1.02	1.02	1.02	1.07	1.15
October	1.05	1.05	1.07	1.11	1.16
November	0.97	1.00	1.04	1.08	1.07
December	0.97	0.96	0.99	0.92	1.01

Entries in Exhibit 37-33 are ADT demand adjustments for a given combination of day and month relative to ADT for a Monday in January. Exhibit 37-34 shows the consolidated table of demand ratios for the example problem.

Exhibit 37-34
Example Problem 8: Consolidated Demand Ratios for I-40 Case Study

Season	**Monday–Wednesday**	**Thursdays**	**Fridays**	**Average**
Winter	0.9969	1.0202	1.0765	1.0175
Spring	1.0813	1.1435	1.1989	1.1173
Summer	1.0689	1.1264	1.1767	1.1020
Fall	1.0267	1.0878	1.1281	1.0592
Average	1.0435	1.0945	1.1451	1.0740

Note that the average demand ratio for this table is greater than 1, which is a result of the base dataset demands being lower than an average day of the year. Since all factors in the above table will be applied as multipliers to the base dataset demand, the relative factors are more pertinent to the analysis than their absolute values.

The probability of each demand level is computed as the number of days represented by the consolidated demand level divided by the total number of days in the reliability reporting period (5 weekdays × 52 weeks, plus one day, or 261 days) (Exhibit 37-35). Deviations from 25% probability for the seasons and from 5% for the individual demand patterns are due to differing numbers of days in the months and differing numbers of weekdays in each month. This particular computation is for calendar year 2010.

Exhibit 37-35
Example Problem 8: Percent Time of Year by Season and Demand Pattern

Season	**Monday–Wednesday (%)**	**Thursdays (%)**	**Fridays (%)**	**Total (%)**
Winter	13.903	4.887	5.255	24.045
Spring	15.179	4.933	4.933	25.045
Summer	15.475	5.022	5.022	25.519
Fall	15.246	5.066	5.079	25.391
Total	59.804	19.907	20.289	100.000

Step 4: Estimate Severe Weather Frequencies

Exhibit 10-15 identifies five weather types (rain, snow, temperature, wind, and visibility) with varying intensity levels that affect the capacity of freeways. Some of these categories or intensity levels have a negligible effect on freeway capacities (4% or less effect) and are consequently neglected in the reliability analysis. On the basis of this criterion, rain under 0.10 in./h, temperature events above –4°F, and all wind events are consolidated into the “non–severe weather” category because of their negligible effects on capacity.

A 10-year weather history of National Weather Service METAR data was obtained for the nearby Raleigh–Durham Airport from Weather Underground. The data were filtered to eliminate "unknown" (–9999) conditions. The time between reports was calculated to obtain the duration of each weather report and to account for missing reports. The data were then classified into the weather categories defined in Exhibit 36-4 in Chapter 36.

http://www.wunderground.com/history/

The percentage of time during the reliability reporting period that each of the weather categories is present was computed by dividing the total number of minutes for each weather category observed in the prior 10 years during the reliability reporting period by the total number of minutes within the reliability reporting period (Exhibit 37-36). The total number of minutes within the reliability reporting period for the 10-year period of weather observations (939,600 min) was computed for this example by multiplying the 6-h study period per day by 60 min per hour by 261 weekdays per year (5 weekdays per week × 52 weeks per year plus 1 day) by 10 years. In cases where multiple weather categories are present (e.g., poor visibility during a snow event), the more severe condition (the one most affecting capacity) is assumed to control, and the event is assigned that weather category.

Exhibit 37-36
Example Problem 8: Percent Time Weather Categories Present on I-40 by Month

	Rain (%)		Snow (%)				Cold (%)	Visibility (%)			
Month	**Med.**	**Heavy**	**Light**	**Light-Med.**	**Med.-Heavy**	**Heavy**	**Severe**	**Low**	**Very Low**	**Min.**	**Non–Severe Weather**
January	1.97	0.00	5.91	0.00	0.00	0.00	0.00	0.00	0.00	0.00	92.12
February	2.72	0.00	0.00	0.00	0.00	0.00	0.00	2.17	0.00	0.00	95.11
March	0.51	0.00	1.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	98.48
April	0.00	0.54	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	99.46
May	1.95	1.95	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	96.10
June	0.51	0.51	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	98.99
July	0.50	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	99.00
August	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00
September	4.26	0.53	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	95.21
October	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00
November	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00
December	0.00	0.00	7.81	0.49	0.00	0.00	0.00	0.00	0.00	0.00	91.71
Average	1.03	0.34	1.23	0.04	0.00	0.00	0.00	0.18	0.00	0.00	97.18

Notes: Med. = medium; Min. = minimal.

Entries are minutes of the identified weather type divided by total minutes of weekday study periods (weekdays, 6-h p.m. peak in this example) for that month. Monthly and annual percentages total 100% for each month and for the full year.

Weather categories with less than 0.1% probability for a given month in the 10-year weather history were dropped from further consideration to manage the number of scenarios. On the basis of this criterion, severe cold, medium–heavy and heavy snow, and very low and minimal visibility were dropped, and the probabilities of all remaining categories were renormalized to add up to 100%. The final set of six weather categories and intensity levels selected for this example problem and their estimated probabilities are shown in Exhibit 37-37.

Exhibit 37-37
Example Problem 8: Estimated Percent Time Weather Events Present on I-40 by Season

Season	Medium Rain (%)	Heavy Rain (%)	Light Snow (%)	LM Snow (%)	Low Visibility (%)	Non–Severe Weather (%)	Total (%)
Winter	1.496	0.000	4.745	0.175	0.679	92.905	100.000
Spring	0.797	0.802	0.352	0.000	0.000	98.049	100.000
Summer	0.335	0.335	0.000	0.000	0.000	99.330	100.000
Fall	1.440	0.180	0.000	0.000	0.000	98.380	100.000
Average	1.017	0.329	1.274	0.044	0.170	97.166	100.000

Note: LM = light to medium.

Seasonal weather probabilities are assumed to apply identically to all demand patterns within the season. (Weather is assumed to be independent of demand pattern within the season.)

Step 5: Estimate Incident Frequencies

Exhibit 10-17 in Chapter 10 identifies the capacity effects of five incident types (shoulder disablement, shoulder accident, one lane blocked, two lanes blocked, and three lanes blocked). The shoulder disablement category was dropped for this example problem because its capacity effects are 1% for facilities with three or more lanes, such as the facility in this example problem.

The HCM analysis method, like all methods limited to a single facility, cannot produce meaningful results for complete facility closures, since any methodology confined to a single facility cannot predict demand rerouting to other facilities. Therefore, the evaluation of incidents in this example is limited to incidents that maintain at least one lane open to traffic. The facility is mostly four lanes in one direction, but there are segments with only two or three lanes.

In this example, generalized crash data were available, but reliable incident logs that indicated incident type by number of lanes closed were not. Five years of crash data were obtained for the 12.5-mi-long eastbound direction of I-40. The data indicated that this portion of I-40 experiences an average of 164.5 crashes per 100 million VMT.

The crash rate for this facility then was expanded to incidents by lane and shoulder closure type by using an expansion factor. A local study comparing shoulder and lane closure incidents with reported crashes found that there were approximately seven incidents involving shoulder or lane closures for every reported crash on I-40.

The expected number of incidents I by month m for the facility is computed as follows:

Equation 37-77

$$I(m) = \frac{CR \times ICR \times VMT(\text{seed}) \times DM(m)}{100 \times 10^6 \times SFDM}$$

where

$I(m)$ = expected number of incidents in month m in the subject direction of travel (incidents);

CR = reported crash rate (crashes per 100 million VMT);

ICR = ratio of incidents to reported crashes (incidents/crash);

VMT(seed) = seed file VMT on facility in subject direction during study period (VMT);

$DM(m)$ = demand multiplier for month m (unitless); and

$SFDM$ = seed file demand multiplier, the ratio of seed file study period demand to AADT for the study period (unitless).

The estimated number of incidents is split into severity types and mean durations by using the values shown in Exhibit 37-38.

Exhibit 37-38 Example Problem 8: Mean Duration and Distribution of Incidents by Severity

Severity	Shoulder Closed	1 Lane Closed	2 Lanes Closed	3+ Lanes Closed	Total
Mean percent of incidents	75.4	19.6	3.1	1.9	100.0
Mean duration (min)	34.0	34.0	53.6	69.6	35.4[a]

Note: [a] Average weighted by the relative frequencies.

Finally, the probability of an incident type is computed as follows:

Equation 37-78

$$PT(t,m) = 1 - e^{-(I(m)\times P(i)\times t_E(i)/t_{SP})}$$

where

$PT(t, m)$ = probability that incident type t is present in month m,

$I(m)$ = expected number of incidents in subject direction in month m,

$P(i)$ = proportion of incidents of type i,

$t_E(i)$ = mean event duration of incidents of type i (min), and

t_{SP} = study period duration (min).

The resulting estimated average percent time with incidents present on the facility is shown in Exhibit 37-39 (results specific to individual demand patterns are too numerous to show here).

Exhibit 37-39 Example Problem 8: Estimated Percent Time Incidents Present on I-40 Eastbound

	Incident Type (%)					
Month	No Incident	Shoulder Closed	1 Lane Closed	2 Lanes Closed	3 Lanes Closed	4 Lanes Closed
January	66.42	23.30	7.06	1.79	1.43	0.00
February	66.36	23.34	7.08	1.79	1.43	0.00
March	65.10	24.18	7.36	1.87	1.49	0.00
April	63.79	25.05	7.66	1.94	1.56	0.00
May	63.87	25.00	7.64	1.94	1.55	0.00
June	64.53	24.56	7.49	1.90	1.52	0.00
July	64.10	24.85	7.59	1.93	1.54	0.00
August	65.30	24.04	7.32	1.86	1.48	0.00
September	65.97	23.60	7.17	1.82	1.45	0.00
October	65.04	24.22	7.38	1.87	1.50	0.00
November	66.79	23.05	6.98	1.77	1.41	0.00
December	68.56	21.86	6.59	1.67	1.33	0.00

The entries in Exhibit 37-39 represent the probability of having a given incident type in each month, calculated from Equation 37-78. The expected number of incidents in a given month was computed by using a crash rate of 164.5 per 100 million VMT, a rounded crash-to-incident expansion factor of 7, and a seed VMT of 330,006 in Equation 37-77. Monthly values total to 100% for each demand pattern.

Step 6: Scenario Generation

Initial Scenario Development

The initial scenario represents a combination of a demand level, a weather type, and an incident type. The demand levels are specified by month and day of week rather than by volume level. This enables the analyst to account partially for the effects of demand on incidents and the effects of weather on demand by using calendar-specific weather and incident probabilities.

The initial estimate of the percent time that each scenario represents of the reliability reporting period is the product of the demand, weather, and incident type percent times that combine to describe the scenario. The assumption is that the percent time of incidents and the percent time of weather are a function of the calendar month and that other correlations between demand, incidents, and weather can be neglected.

Equation 37-79

$$PT(d,w,i) = PT(d) \times PT(w|d) \times PT(i|d)$$

where

$PT(d,w,i)$ = percent time associated with demand pattern d with weather type w and incident type i,

$PT(d)$ = percent time of demand pattern d within the reliability reporting period,

$PT(w|d)$ = percent time of weather type w associated with demand pattern d, and

$PT(i|d)$ = percent time of incident type i associated with demand pattern d.

Exhibit 37-40 shows the initial estimated scenario percent times before the details as to starting time, location, and duration of incidents and weather have been specified. This table shows the results only for normal weather conditions. Similar computations and results are obtained for the other weather conditions. *Note that the initial probabilities for all weather and incident conditions must sum to the percent time for each demand pattern within each season*.

For computing percent time of incident type i associated with demand pattern d, the probabilities presented in Exhibit 37-40 are averaged and weighted by the number of days each demand pattern has in the calendar.

Exhibit 37-40
Example Problem 8: Percent Times for Incident Scenarios in Non–Severe Weather

Season	Day	No Incident (%)	Shoulder Closure (%)	1 Lane Closed (%)	2 Lanes Closed (%)	3 Lanes Closed (%)	Subtotal Non–Severe Weather (%)	Subtotal Severe Weather (%)	Total (%)
Winter	M-W	8.847	3.005	0.909	0.230	0.184	13.176	1.000	14.176
	Thu	3.110	1.053	0.319	0.081	0.064	4.626	0.355	4.981
	Fri	3.344	1.135	0.343	0.087	0.070	4.979	0.385	5.364
Spring	M-W	9.660	3.710	1.132	0.287	0.230	15.019	0.307	15.326
	Thu	3.139	1.210	0.369	0.094	0.075	4.887	0.094	4.981
	Fri	3.139	1.210	0.369	0.094	0.075	4.887	0.094	4.981
Summer	M-W	9.848	3.724	1.135	0.288	0.230	15.226	0.100	15.326
	Thu	3.196	1.212	0.370	0.094	0.075	4.946	0.035	4.981
	Fri	3.196	1.212	0.370	0.094	0.075	4.946	0.035	4.981
Fall	M-W	9.702	3.468	1.053	0.267	0.213	14.704	0.239	14.943
	Thu	3.224	1.155	0.351	0.089	0.071	4.889	0.092	4.981
	Fri	3.232	1.161	0.353	0.089	0.072	4.907	0.074	4.981
Total	All	63.637	23.255	7.073	1.794	1.434	97.194	2.806	100.000

All entries are percent time within the reliability reporting period when the specified conditions are present on the facility. Percentages for rain, snow, and low-visibility conditions are not shown. Percentages are computed by using Equation 37-79 and percentages from Exhibit 37-35, Exhibit 37-37, and Exhibit 37-39.

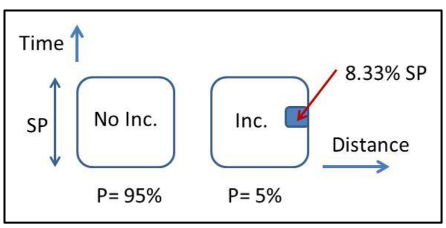
Study Period Scenario Development

The estimated percent times for each condition must be converted to scenario probabilities so that scenario performance results can be appropriately weighted when overall travel time reliability is computed.

Not all inclement weather scenarios (rain, snow, etc.) and incident scenarios involving a shoulder or lane closure persist for the entire duration of the study period. Therefore, the probabilities of each of these scenarios must be weighted to ensure that these scenarios sum to the appropriate total percentage times predicted for each of these events.

As an example to illustrate the concept, consider a single nonrecurrent congestion event—say an incident. Incident logs obtained from the responsible state agency indicate that during the study period (say 6 h) for all weekdays in a year, the probability of an incident was 5%. This situation would be modeled as two separate initial scenarios each 6 h long, one without an incident with an assigned 95% probability and the other with an incident with 5% probability. A continuous 6-h incident is not (and definitely should not be) modeled as a full scenario. This is where the initial scenario definition ends. To model the effect of a scenario, additional details are needed, such as the duration of the incident. If the incident lasted for 30 min, the overall incident probability inside the incident study period would be computed as (0.5 h) / (6 h) = 8.33%. The two initial scenarios and probabilities are illustrated in Exhibit 37-41.

Exhibit 37-41
Example Problem 8: Schematic of Two Initial Scenarios and Probabilities



Note: Inc. = incident.

This modeling scheme clearly results in a bias in the analysis, since much of the initial scenario with the incident actually contains many time periods where there are no incidents. This is important since all probabilities are computed timewise. If one accepts the above definitions, the resulting probability of an incident would actually be = 0.0833 × 0.05 = 0.416%, which is much less than the 5% incident probability observed on the facility. Similarly, the probability of a nonincident would be 99.58%, not 95%. These are crucial differences in probabilities that will have a significant impact on the resulting travel time distribution. The differences between the stated probability and its correct value also increase when the number of scenarios (inevitably) increases.

The simplest approach to overcoming these differences is to readjust the relevant initial scenario probabilities so that the original incident probability is honored in all cases. This can be done by using a simple equation to estimate the true study period scenario probability Π from Equation 37-80.

Equation 37-80

$$\Pi = P \times \frac{\text{SP duration (min)}}{\text{Event duration (min)}}$$

The probability Π = 0.05 × (6 × 60) / 30 = 0.60, or 60% for the study period incident scenario, and by the rule of complementary probability, 40% for the nonincident scenario, a large swing from the initial probabilities. In fact, the algorithm results in lowering the probability of no-event scenarios and transferring those probabilities to the event-based scenarios. The overall probability of an incident is now 0.60 × 0.0833 = 5%, which was the originally stipulated incident probability.

An interesting twist occurs if the average event duration is too short (or the study period duration is excessively long). In the example above, if the incident duration was 15 min, Equation 37-80 would yield an adjusted probability of 1.2. This implies that there is an incompatibility between the stated probability and the average incident duration. In this case, the duration must be adjusted upward in intervals of 15 min (corresponding to analysis period lengths) until the probability drops below 1. In this example, the next interval would be a 30-min incident, with the probabilities as computed in the previous paragraph.

Exhibit 37-42 shows the final estimated study period scenario probabilities for the scenarios involving non–severe weather. Not shown are similar tables for rain, snow, and low-visibility conditions used to derive the severe weather column.

Exhibit 37-42
Example Problem 8: Estimated Incident Study Period Scenario Probabilities After Adjustment

		Non–Severe Weather					Weather Subtotals		
Season	Day	No Incident (%)	Shoulder Closed (%)	1 Lane Closed (%)	2 Lanes Closed (%)	3 Lanes Closed (%)	Non–Severe (%)	Severe (%)	Total (%)
Winter	M-W	0.008	4.006	3.637	1.373	0.871	9.896	4.28	14.176
	Thu	0.027	1.404	1.274	0.481	0.305	3.491	1.49	4.981
	Fri	0.018	1.513	1.374	0.519	0.329	3.753	1.61	5.364
Spring	M-W	0.431	4.947	4.529	1.706	1.083	12.695	2.63	15.326
	Thu	0.153	1.614	1.478	0.557	0.354	4.155	0.83	4.981
	Fri	0.153	1.614	1.478	0.557	0.354	4.155	0.83	4.981
Summer	M-W	0.581	6.384	4.541	1.721	1.098	14.324	1.00	15.326
	Thu	0.161	2.078	1.478	0.560	0.357	4.634	0.35	4.981
	Fri	0.161	2.078	1.478	0.560	0.357	4.634	0.35	4.981
Fall	M-W	0.167	5.946	4.213	1.591	1.012	12.929	2.01	14.943
	Thu	0.206	1.732	1.403	0.529	0.336	4.206	0.78	4.981
	Fri	0.087	1.991	1.411	0.533	0.339	4.361	0.62	4.981
Total	All	2.154	35.305	28.293	10.687	6.795	83.235	16.77	100.00

Notes: M = Monday; W = Wednesday; Thu = Thursday; Fri = Friday.

Operational Scenario Development

The incident starting time, duration, and location must be specified for incident scenarios. To ensure that a representative cross section of performance results is obtained, each incident study period scenario involving a closure of some kind is subdivided into 18 possible operational scenarios (two start times, three locations, and three durations):

- Starting at the beginning or the middle of the study period;
- Located at the beginning, middle, or end of the facility; and
- Occurring for the 25th, 50th, or 75th percentile highest duration for a given incident type.

Note that some operational scenario options may be prohibited. For example, if the beginning, middle, or end of the facility only has three lanes, the three-lane closure scenario is not modeled for this condition. In this case, the operational scenario is removed from the list of operational scenarios and its probability is assigned proportionally to the remaining operational scenarios.

Each of the 18 incident operational scenarios is considered equally probable within the study period scenario. Thus each operational scenario is given 1/18th the probability of the study period scenario for the incident type.

For example, the study period scenario associated with Demand Pattern 1 (Monday–Wednesday in winter), with non–severe weather, and with a shoulder closure has a 4.00645% probability of occurrence. Then, the operational scenario associated with the incident starting at the beginning of the study period, in the middle segment, and for an average duration will have a 4.00645% / 18 = 0.22258% probability of occurrence.

The starting time and duration must also be specified for the severe weather scenarios (rain, snow, etc.). Weather is assumed to apply equally across the entire facility. To ensure that a representative cross section of performance results is obtained, each severe weather study period scenario is subdivided into two possible operational scenarios:

- Severe weather beginning at the start of the study period, and
- Severe weather beginning in the middle of the study period.

Each weather operational scenario for each severe weather study period scenario is given one-half the probability of the study period scenario for the weather type.

For example, the study period scenario associated with Demand Pattern 1 (Monday–Wednesday in winter), with light snow weather, and with no incident has a 0.22294% probability of occurrence. Therefore, the operational scenario associated with the weather event starting at the beginning of the study period will have a 0.22294% / 2 = 0.11147% probability of occurrence.

Removal of Improbable and Infeasible Scenarios

Theoretically, the procedure can generate up to 22,932 operational scenarios for the subject facility. Many of these may have exceptionally low or near-zero probability. In addition, some may be infeasible—for example, a two- or three-lane closure on a two-lane freeway segment. For this example, the infeasible and zero-probability operational scenarios were removed from the reliability analysis. This translates to an inclusion threshold of near "zero," meaning that all scenarios with probability greater than zero are included in the analysis. This leaves 2,058 scenarios to be used in evaluating travel time reliability for the I-40 facility, as shown in Exhibit 37-43.

Exhibit 37-43
Example Problem 8: Final Scenario Categorization

Scenario Type	Number of Operational Scenarios	Percent of Total
No incidents and non–severe weather	12	0.6%
No incidents and severe weather	66	3.2%
Incidents and non–severe weather	528	25.7%
Incidents and severe weather	1,452	70.6%
Total	2,058	100.0%

The percentages shown here are *not the probabilities of occurrence.* They indicate the proportionate number of HCM analyses that will be performed on each scenario type for the reliability analysis. This is because each 6-h study period for incident and weather scenarios contains many 15-min analysis time periods characterized by fair weather and no-incident conditions. The numbers shown in Exhibit 37-43 ensure that the initial incident and weather probabilities are honored.

Step 7: Apply the HCM 2010 Analysis Method

The HCM 2010 freeway facility analysis method is applied to each of the 2,058 operational scenarios with capacity and speed–flow curve adjustments appropriate for each scenario.

The standard HCM freeway speed–flow curves are not appropriate when incidents and weather are modeled. Therefore, as described in Chapter 37, a modified version of Equation 25-1 from Chapter 25, Freeway Facilities: Supplemental, is used in combination with the combined CAFs and SAFs to predict basic freeway segment performance under incident and severe weather scenarios:

$$S = (FFS \times SAF) + \left[1 - e^{\ln\left((FFS \times SAF) + 1 - \frac{C \times CAF}{45}\right) \times \frac{v_p}{C \times CAF}}\right]$$

where

S = segment speed (mi/h),

FFS = segment free-flow speed (mi/h),

SAF = segment speed adjustment factor,

C = original segment capacity (pc/h/ln),

CAF = capacity adjustment factor, and

v_p = segment flow rate (pc/h/ln).

Capacity adjustment and free-flow speed adjustment factors for weather are selected for the I-40 facility on the basis of its free-flow speed of 70 mi/h, as shown in Exhibit 37-44:

Exhibit 37-44
Example Problem 8: Free-Flow CAFs and SAFs for Weather on I-40

	Medium Rain	Heavy Rain	Light Snow	Light–Medium Snow	Low Visibility	Non–Severe Weather
CAF	0.91	0.84	0.95	0.90	0.90	1.00
SAF	0.93	0.92	0.87	0.86	0.94	1.00

The CAFs for segments with incidents on I-40 are selected on the basis of the number of lanes in the subject direction for the segment where the incident is located (Exhibit 37-45). The free-flow SAF for incidents is set at 1.00. The factors in Exhibit 37-45 do not include the effect of the number of closed lanes. In other words, both the number of lanes closed and the resulting capacity per open lane on the segment must be specified by the user.

Exhibit 37-45
Example Problem 8: CAFs per Open Lane for Incidents on I-40

No. of Directional Lanes	No Incident	Shoulder Closure	1 Lane Closed	2 Lanes Closed	3 Lanes Closed
2	1.00	0.81	0.70	N/A	N/A
3	1.00	0.83	0.74	0.51	N/A
4	1.00	0.85	0.77	0.50	0.52

Note: N/A = scenario not feasible.

For scenarios with both incidents and severe weather, the CAFs are multiplied to estimate their combined effect. CAFs and SAFs are also applied to the merge, diverge, and weaving segments along the facility.

Step 8: Quality Control and Error Checking, and Inclusion Thresholds

Quality control and error checking start with the base scenario (seed file) and proceed to the nonincident, non–severe weather scenarios.

Error Checks of the Seed File

Quality control for 2,058 scenarios is difficult, so it is recommended that the analyst focus on error checking and quality control on the single initial HCM seed file that is used to generate the scenarios. The file should be error checked to the analyst’s satisfaction to ensure that it accurately represents real-world congestion on the freeway facility under recurring demand conditions with no incidents and under non–severe weather conditions. The same criteria for error checking should be used as for a conventional HCM analysis, but with the recognition that any error in the seed file will be crucial, because it will be multiplied 2,058 times by the scenario generator.

Error Checks for Nonincident and Non–Severe Weather Scenarios

Once the seed file has been error checked, the denied entry statistic is examined for each of the scenarios not involving severe weather or incidents. The number of vehicles denied entry to the facility (and not stored on one of its entry links or ramps) should be as near zero as possible for non–severe weather, nonincident conditions. If feasible, the entry links and ramps should be extended in length to ensure that all vehicle delays for these *demand-only* scenarios are accounted for within the facility or its entry links and ramps.

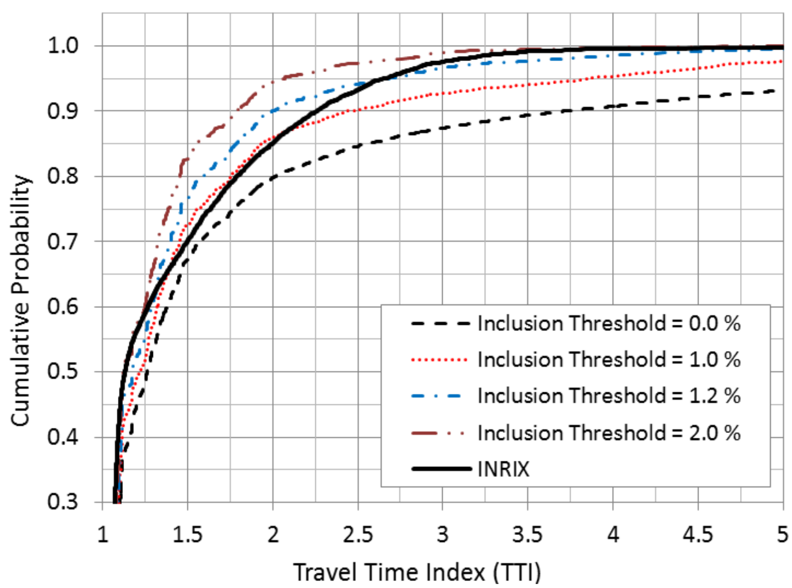
The number of vehicles queued on the facility (and its entry links and ramps) during the first analysis period should be nearly the same as the number of vehicles queued in the last analysis period. If necessary, the study period should be extended with one or more artificial analysis periods to ensure that there is not a great change in the number of vehicles queued within the facility between the beginning and the end of the study period. Ideally, the number of vehicles queued in the first and last analysis periods should be zero.

Inclusion Thresholds

As mentioned earlier, the procedure can generate several thousand scenarios, many of which may have exceptionally low or exactly zero probability. In addition, some scenarios may be infeasible. The infeasible scenarios are automatically filtered out by the freeway scenario generation procedure. The scenarios with extremely low probability are not expected to be observed in the field in a single year; however, they are included in the predicted TTI distribution (with an inclusion threshold of zero). This makes the comparison of the predicted and observed distributions hard to interpret. In addition, these scenarios tend to have exceptionally large TTI values that significantly shift the tail of the cumulative distribution to the right (i.e., toward higher TTI values). These scenarios may also result in demand shifts in the real world that are not directly accounted for in the freeway reliability method.

Thus, the procedure allows the user to specify an "inclusion threshold" to include only scenarios with probability larger than the threshold specified in the analysis. For example, an inclusion threshold of 1.0% means that only the scenarios with probability larger than 0.01 are considered in the analysis. Exhibit 37-46 presents the TTI cumulative distributions for four inclusion threshold values for the subject facility as well as the observed TTI distribution obtained from a probe data warehouse. For the subject facility, including all the scenarios with a nonzero probability in the analysis (i.e., inclusion threshold = zero) resulted in a general overestimation in the TTI cumulative distribution. Increasing the threshold to 1.0% brought the TTI distribution much closer to the observed distribution. An inclusion threshold of 1.2% resulted in generally matching PTI values for the predicted and observed TTI distributions. Inclusion thresholds larger than 1.2% yielded a general underestimation in the TTI distribution.

Exhibit 37-46
Example Problem 8: Travel Time Distribution Results for Different Inclusion Thresholds



Increasing the value of the inclusion threshold reduces the number of scenarios and consequently the run time; however, at the same time it reduces the percentage of feasible scenarios covered (Exhibit 37-47). In other words, the larger the value of the inclusion threshold, the higher the number of scenarios excluded from the analysis and the lower the number of feasible scenarios covered.

Exhibit 37-47
Example Problem 8: Number of Scenarios and Coverage of Feasible Scenarios

Inclusion Threshold (%)	Number of Scenarios	Percent Coverage of the Distribution
0.00	2,058	100.00
0.01	1,004	99.71
0.10	496	97.46
1.00	264	89.63
1.20	210	85.07
1.30	174	82.55
2.00	84	75.91
3.00	81	67.04
4.00	4	37.32

As shown in Exhibit 37-47, the number of scenarios drops significantly as the value of the inclusion threshold increases. Going from an inclusion threshold of 0.00% to 0.01% eliminated half of the scenarios and decreased the coverage of the distribution by only 0.29%. This means that more than 1,000 of the scenarios contributed to only 0.29% of the TTI distribution.

Step 9: Interpreting Results

This step compares the reliability results with the agency's established thresholds of acceptability and the diagnoses of the major contributors to unreliable travel times on I-40. The core and supplemental reliability performance measures computed for the example problem are shown in Exhibit 37-48. Each observation from the I-40 data represents a 15-min mean TTI. For example, the PTI value of 5.34 is interpreted as the TTI associated with the highest 5th percentile analysis period out of *all* analysis periods covered in the reliability reporting period (in this case, 2,058 × 24 = 49,392 periods). When certain TTI parameters are compared with each other, it is critical that they be computed for identical time periods.

Exhibit 37-48
Example Problem 8: Reliability Performance Measure Results for I-40

Measure	Value
TTI_{mean}	1.97
PTI	5.34
TTI_{80}	2.03
Semi–standard deviation	2.41
Failure/on-time (40 mi/h)	0.26
Standard deviation	2.21
Misery index	9.39
Reliability rating	54.0%

The PTI was computed by finding the 95th percentile highest analysis period mean facility TTI for the subject direction of travel. The TTI_{80} was simply the 80th percentile highest TTI (each of which is the average TTI for the analysis period for that scenario).

The semi–standard deviation was computed by subtracting 1 (in essence, the TTI at free-flow speed) from each of the facility mean TTIs for each of the analysis periods, squaring each result, weighting each result by its probability, and summing the results. The square root of the summed results was then taken to obtain the semi–standard deviation.

$$SSD = \sqrt{\sum_{s} P_s \left(TTI_{\mathrm{mean},s} - 1\right)^2}$$

where

SSD = semi–standard deviation (unitless),

P_s = probability for analysis period s, and

$TTI_{\mathrm{mean},s}$ = facility mean travel time index for analysis period s (unitless).

The failure/on-time index was computed by summing the probability of all analysis periods that have an average speed less than 40 mi/h:

$$FOTI = \sum_{s \in S_{40}} P_s$$

where

$FOTI$ = failure/on-time index (unitless), and

S_{40} = set including all analysis periods with average speeds less than 40 mi/h.

The standard deviation was computed by subtracting the average analysis period TTI (over the reliability reporting period) from each of the facility average TTIs for each of the analysis periods, squaring each of the results, weighting each result by its probability, and summing the results. The square root of the summed results was then taken to obtain the standard deviation.

$$SD = \sqrt{\sum_{s} P_s \left(TTI_{\mathrm{mean},s} - \overline{TTI}\right)^2}$$

where SD is the standard deviation (unitless), $\overline{TTI}$ is the average analysis period TTI over the reliability reporting period, and other variables are as previously defined.

The misery index was computed by averaging the highest 5% of travel times divided by the free-flow travel time, or in other words by averaging the highest 5% of TTIs.

$$MI = \frac{\sum_{s \in T_5} P_s TTI_{\mathrm{mean},s}}{\sum_{s \in T_5} P_s}$$

where MI is the misery index (unitless), T_5 is the set including the highest top 5% of TTIs, and other variables are as previously defined.

During the scoping process for this example, the agency selected the TTI_{mean} and the PTI as its reliability performance measures for this study. The calculated TTI_{mean} and the PTI are compared with the thresholds of acceptable performance established at the start of this example problem (Exhibit 37-49). Both statistics fall above the 90th percentile among freeways in weekday a.m. peak period in the SHRP 2 L08 dataset and consequently do not meet the agency's threshold of acceptability for reliable performance.

Exhibit 37-49
Example Problem 8:
Evaluation of TTI and PTI Results for I-40

Statistic	I-40 Reliability	Agency Threshold of Acceptability	Conclusion
TTI_{mean}	1.97	<1.78	Unsatisfactory
PTI	5.34	<3.34	Unsatisfactory

The agency's congestion management goal is to operate its freeways at better than 40 mi/h during 50% of the peak periods of the year and better than 25 mi/h during 95% of the peak periods during the year. The TTI_{mean} shown in Exhibit 37-49 is recomputed for 40 mi/h and is found to be 1.13 (Exhibit 37-50). This value is larger than 1.00, which means that the agency has not achieved this congestion management goal for the I-40 freeway. Similarly, the PTI shown in Exhibit 37-49 is recomputed for 25 mi/h and found to be less than or equal to 1.00, meaning that this goal was achieved.

Exhibit 37-50
Example Problem 8:
Evaluation of Policy TTI and PTI Results for I-40

Statistic	I-40 Reliability (at 70 mi/h)	I-40 Reliability (at 40 mi/h)	I-40 Reliability (at 25 mi/h)	Agency Threshold of Acceptability	Conclusion
Policy index	1.97	1.13	0.68	≤1.00	Unsatisfactory

Remarks

As noted in the Inclusion Thresholds section, a comparison of the TTI estimated by using this chapter's travel time variability methodology with the TTI obtained from probe data for the subject facility found that TTI was generally overestimated when all scenarios were included in the analysis. This is because (*a*) the methodology does not automatically adjust demand to reflect shifts in demand when rare but severe incidents or weather conditions occur and (*b*) not all of the rare events accounted for in the HCM method may occur in a given year of field data. Excluding the rarest 1.2% of scenarios resulted in a much better agreement between the HCM results and 1-year field measurements for this particular facility (different inclusion thresholds may produce the best agreement on other facilities).

Therefore, analysts should keep in mind that using direct sources of TTI data may yield different results or a different conclusion. Analysts should also keep in mind that even though a lower TTI or PTI than predicted by the HCM method may be observed on a given facility as a result of demand-shifting, the field-measured values do not necessarily reflect the longer travel times experienced by the drivers who take other routes or incur the inconvenience of making their trips at a different time than desired.

7. REFERENCES

Some of these references are available in the Technical Reference Library in Volume 4.

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