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Evaluation of Intersection Properties Using MARS Method for Improving Urban Traffic Performance: Case Study of Tekirdağ, Turkey

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ABSTRACT

Increasing urban traffic performance is a technical problem that has been investigated by many researchers these days. Traffic performance can be increased in many ways, as part of the transportation planning process, on smaller scales, or with different methods and techniques. The determination of traffic intervention areas in urban transportation planning is an intervention type that determines the rate at which the traffic performance will increase. Although transportation planning is an integrated issue, the type of traffic modification and prior intervention on intersections are often determined with partitive paradigms and strategies. It is a significant opportunity for decision makers to be informed in advance of the effects of intersection characteristics on the overall traffic performance. However, it is not an attempted or tested concept to perform a general assessment of the impact of the intersection characteristics on the overall performance of the intersections. In this study, a four-stage integrated analysis including the multivariate adaptive regression splines (MARS) method is proposed for the overall traffic performance evaluation. The traffic characteristics of intersections are first indexed and categorized. The intersection performance results are then obtained using the VISSIM traffic simulation software. Subsequently, the relationship between them is determined with the MARS method, and the effects of the intersection characteristics on the traffic performance are investigated. Tekirdağ, a metropolitan city located in northwestern Turkey, is selected for the case study. According to the obtained simulation results, the suggestions related to the development of intersection performances are made and tested.

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1. INTRODUCTION

In the last decades, the spread of land use and motorized travel demand in urban areas have increased based on the growing urbanization. On the other hand, people are spending more time in traffic owing to the increasing travel distances and durations even on normal (steady state) traffic conditions. Considering the typical incidents (i.e., accidents, car breakdowns, lane blockages from construction activities, bad weather conditions), traffic flow is interrupted and unpredictable delays occur [1]. In this context, many researchers have handled delay and travel time minimization problems on the network and arterial levels. Most typical studies on the network level focus on the transportation network design problem, in which some traffic control strategies are introduced to calculate the intersection signal timings more accurately, or topologies of the network elements (i.e., parking places, road closure schemes, lane addition, lane allocation) are redesigned [2-8]. On the other hand, the performance analyses of urban arterials are primarily evaluated in terms of the average travel time, which is a function of signal timing parameters of adjacent intersections and traffic flow patterns under different levels of congestion [9-10]. Therefore, several studies focus on signal timing and offset optimization on urban arterials [11-15]. When viewed from this aspect, intersections appear to be the key point to provide shorter travel times and decrease the level of congestion on the roads. Because the intersections are the most critical components of the road transportation systems, they must be designed and operated based on the advanced methodologies to determine the most appropriate solution. Thus, the project level requirements can be satisfied by addressing the site constraints [16]. In the relevant literature, congestion management strategies have widely been investigated based on the geometric designs or operational improvements of signalized intersections (i.e., cycle time determination, green split calculations, phase planning).

Intersection geometry and physical element improvements may be interpreted as the most recognized intersection intervention types. The total delay time, queue length, capacity, and safety performance of an intersection is directly related to the geometric design itself. Otković and Dadić [17] compared the delays at a roundabout and a conventional signal-controlled intersection in Osijek city. They found that the delay times could be decreased significantly at roundabouts in comparison with the signalized intersections. Furthermore, a number of studies outlined that the roundabouts provided safer driving environments by decreasing all crashes from 21% to 61% [18-20]. While the increasing trend on replacing conventional signalized intersections with roundabouts has continued, designing unconventional intersections has also been emphasized by researchers [21-30]. As reported in the previous research, geometrically different designed intersections provide different levels of operational and safety performance. Apart from the geometric adjustments on isolated intersections via converting them into roundabouts or unconventional types, signal timing improvements has widely been studied in the past. Lan [31] proposed a new cycle time calculation approach based on nonlinear regression analysis to reveal the relationship between cycle time and traffic flow pattern based on the total lost time, critical flow ratio, and duration of analysis period. Results of the study showed that the generated optimal cycle length is only 5.7% deviated from the analytical solution. Talmor and Mahalel [32] proposed a signal timing design method for an isolated intersection under severe congestion conditions. They showed that designing the signal timing parameters by considering the throughput function, instead of the saturation flow function, might increase the discharge capacity of a signalized intersection. Yu et al. [33] presented a multi-objective optimization problem including capacity, delay time, number of stops, and emissions with their related weights determined by the fuzzy compromise programming approach. In their study, the objective function value is minimized using genetic algorithm, and the results showed that the capacity of the intersection could be improved by reducing the vehicle delays and number of stops. As shown above, several studies concerning intersection performance improvements have focused on either the intersection geometry or signal timing calculations based on prior decisions. In other words, the planner has already decided to convert a signalized intersection into a roundabout or an unconventional intersection; subsequently, the research is built on this prior decision. Likewise, the planner may have decided to increase the performance of a signalized intersection by only changing the stage plan, cycle time, and green times. In either case, it is assumed that the planner can provide the right decision. However, considering a significant variety of factors affecting the performance of an intersection, developing an integrated approach would be useful for policy makers and planners because prejudiced decisions may lead to time loss or missing a better solution alternative. This approach may be developed using regression models by identifying the intersection performance as the dependent variable within different perspectives (i.e., average speed, travel time, delay time, and number of stops). Meanwhile, several factors affecting the intersection performance may be treated as the independent variables. Therefore, the most important determinants of the intersection performance would be identified and policy makers can be supported for the efficient use of resources.

This study employs a novel estimation technique, the multivariate adaptive regression spline (MARS) model that has been widely applied in many scientific fields. MARS is a method providing flexibility to consider nonlinear effects of explanatory variables using the partial adaptation of spline functions [34]. Additionally, MARS can provide threshold values of explanatory variables where the effects on dependent variables considerably change [35]. As the intersection performance depends on miscellaneous factors such as traffic characteristics (volume, composition, moving directions, etc.), control type (signalization, give way, etc.), geometry (lane number and width, dimensions, medians, etc.) and immediate surroundings (close intersections, bus stops, etc.), linear approaches cannot adequately predict the intersection performance. Additionally, parametric predictions including threshold values of independent variables that should not be exceeded in intersection design (maximum cycle time, maximum roundabout diameter, etc.) are essential to obtain the basic principles for practitioners. Thus, more accurate and substantive results may be obtained in performance prediction using the MARS approach. As mentioned before, studies on intersection performance improvements are based on the assumption that intersection control type and geometric structure are predetermined. However, improving a particular intersection depending on the parameters initially adopted may prevent the planner from making a much more efficient planning. By using the proposed approach in this study, it may be possible to simultaneously evaluate a great variety of data reflecting geometric characteristics, control type and traffic flow patterns in terms of the performance of a given intersection. Once the model results are justified on a valid sample size, intersection performance estimation can be obtained without using expensive and time-consuming micro simulation models. Therefore, it is expected to bring a new perspective, which may be identified as a holistic point of view, to the investigation of intersection performance analysis.

In this context, a four-step integrated approach is developed to determine several independent variables' (i.e., intersection control type, intersection geometry type, number of legs, number of enter/exit lanes, signal timings, traffic flow characteristics, number and distance of bus stops around, intersection size) impact on eight intersection performance indicators by employing the MARS model. The values of the performance indicators are obtained using microsimulations by the VISSIM software. Based on the modelling results, the most efficient relationships between the intersection properties and performance indicators are determined, and explanatory information on how to achieve targeted improvements in the intersection performance is provided for policy makers and planners. At the final step of the proposed approach, a demonstration is provided to show that the MARS model predictions may effectively be used to examine and improve the performance of an existing intersection.

The remainder of the paper is organized as follows: The next section presents the method and study area. The analyses are provided in section 3 including the indexing of intersections, the MARS model results, and the selection and testing of intersection design parameters. Finally, section 4 presents the conclusions and some suggestions for future directions.

2. METHOD & STUDY AREA

2.1. Method

The aim of this study is to offer an effective traffic improvement planning by considering the intersection characteristics and performance on decision levels. Hence, a stepwise paradigm has been offered and each level has been defined, as shown in Fig. 1.

Step 1; starts with the description and indexing of intersection features. Intersections have many characteristics, and the determination of those characteristics to use them for generating intersection modification strategies is substantial. Those characteristics may be the leg green times according to their directions, saturated leg flows, traffic volumes and ratios according to their types and directions, saturation rate, square diameters, square lane numbers, average approach square existence, existence of roundabouts, average number of lane widths, existence of bus stop and their distances to the intersections, number of lanes, existence of intermediate refuge, turn pads, existence of intersections nearby, dimensions of intersection, number of legs, phase numbers, signal cycle times, and signaling status. These can be grouped into four primary parts: traffic-, geometric-, and control-related features and immediate surroundings. The derived intersection characteristics for the study are shown in Tables 1a and 1b. While the characteristics, especially the control-related ones are specific, most of the traffic-related and geometric parameters are generic except the roundabout diameter, saturation flow, etc. Traffic-related parameters are generally derived according to the volume moves for different directions (through passing, right turn, left turn) and their average percentages. Passenger car equivalent (PCE) volumes are obtained using the coefficients suggested in the Highway Capacity Manual (HCM) 2010 [36]. The geometric layout of intersections is also considered in detail with the lane width and number, existence of turning bays and medians, distances between stop lines, etc. Control-related characteristics are generally based on signalization such as average green time and their percentages for each movement, number of phases, etc. The critical components in the immediate surrounding of each intersection are also described. In particular, the existence, number and distance of close intersections, and bus stops are indexed. As stated in HCM 2010, transit buses that stop for picking up or discharging passengers within 75 m of the stop line, block the traffic flow. Thus, the number and distance of upstream and downstream bus stops within 75 m of the stop line are indexed. Furthermore, the number of upstream and downstream intersections within 400 m of the stop line is considered during the modeling process by considering a 50 km/h progressive speed for urban areas, where the traffic volumes are spread over several streets [37]. The mentioned parameters may be correlated with the intersection performance results and thus the relation between performance and characteristics may be established. Hence, policy makers may use those results for decision making and scenario generation processes of transportation planning at low levels.

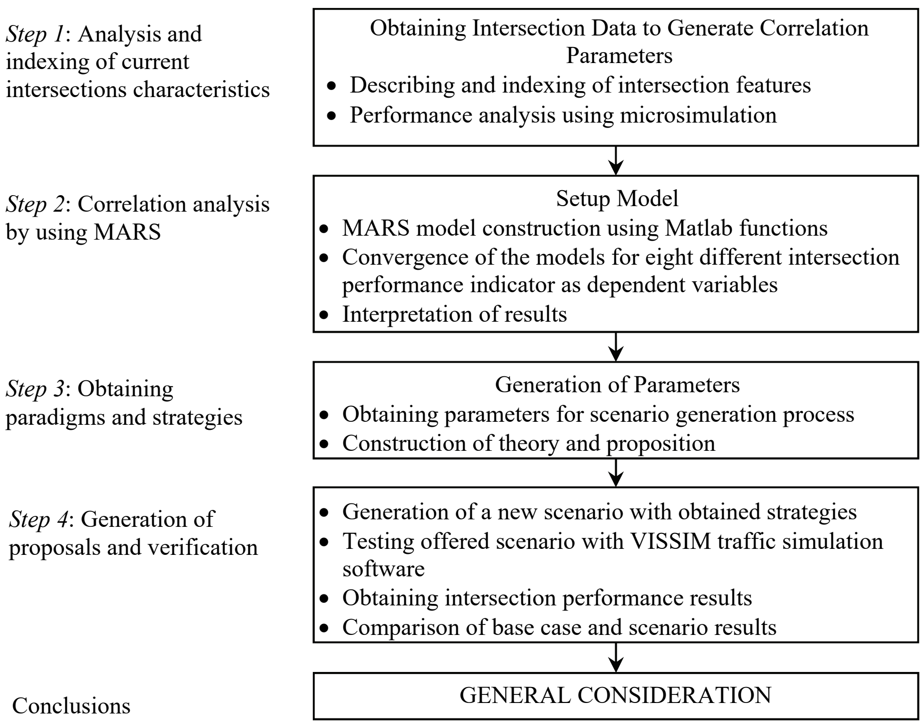

Fig. 1 - Flowchart of the traffic improvement stepwise paradigm

At the second stage of Step 1 in the stepwise paradigm, intersection performances are obtained using microsimulations. The VISSIM traffic simulation software is preferred for the study. It is utilized for visual analysis, and to measure the overall intersection performance. VISSIM was originally developed at the University of Karlsruhe, Germany. VISSIM may be used to analyze traffic and transit operations, traffic composition, bus stops, traffic signals, and evaluating different alternatives under various scenarios. It is a time-step, micro and behavior-based simulation model, which is developed to model traffic operations and analyze traffic performance. The simulation necessitates the input parameters like the geometry of traffic lanes, vehicle composition, speed, traffic volumes and movements at each intersection leg, vehicle routes in the intersection and conflict areas. The measurement parameters are the average delay time per vehicle (s), average speed (km/h), average number of stops per vehicles, average stopped delay per vehicle (s), total delay time (h), number of stops, total stopped delay (h), and total travel time (h). The mentioned software is a microscopic multimodal traffic flow simulation software package developed by PTV Planung Transport Verkehr AG in Karlsruhe [38].

Step 2; consists of a correlation analysis using the MARS approach. MARS is a multivariate nonparametric and nonlinear regression method, introduced by Friedman [39, 40]. The model consists of spline basis functions, where the basis functions and the parameters associated with each one (product degree and knot locations) are automatically determined by the data. This procedure is motivated by the recursive partitioning approach to regression and shares its attractive properties. It has more power and flexibility to model relationships that are nearly additive or involve interactions. Additionally, the model can be represented in a form that separately identifies the additive contributions and those associated with different multivariable interactions [39].

Because of the promising prediction power and interpretation simplicity of the MARS method, it is preferred in novel models, specifically where the nonlinearity between predictors and response are under question. Unlike other prediction models, a prior assumption for the relationship between dependent and independent variables is not required. Additionally, MARS is not a black-box model as much as the other nonlinear prediction techniques, e.g., artificial neural networks, fuzzy-logic, etc. because it provides an interpretable equation that includes coefficients according to the intervals produced by the model structure [35].

In recent years, transportation investigations use the MARS method in many studies such as accident analysis [41-43] and air passenger demand forecasting [34]. Although the application of MARS is limited in traffic engineering, the capability and interpretability of this approach is clearly introduced especially in traffic flow prediction [44, 45]. In these studies, short-term traffic flow prediction on interstate freeway segments is performed by considering spatio-temporal effects in the MARS method, and its superior prediction accuracy is revealed by comparing with many other advanced modeling techniques such as the parametric model autoregressive integrated moving averaging (ARIMA) and the kernel method support vector regression. This encourages the use of MARS in intersection-related analyses where multiple varieties of short run affects are under question.

In the MARS method, the relation between dependent and independent variables is described in intervals by piecewise regression functions. The term “piecewise” means that MARS divides the space of predictors into multiple knots and subsequently fits a spline function between them [42]. The general MARS function can be expressed using the following equation (1):

Table 1a - List of explanatory (1-55) variables examined in MARS models.

No	Variable Name	Short Name	Description
1	Intersection control type	Cont	1: signalized, 0: unsignalized
2	Intersection geometry type	Geo	1: roundabout, 0: others
3	Cycle time*	Cyc	If the intersection is signalized (sec)
4	Number of phases*	No.phases	If the intersection is signalized
5	Number of legs	No.legs	
6	Number of entering flows	No.enter	
7	Intersection dimension in East-West direction	Dim_EW	Distance between E-W bound stop lines (m)
8	Intersection dimension in North-South direction	Dim_NS	Distance between N-S bound stop lines (m)
9	Existance of close intersection	Ex_close	yes:1, no:0 (closer than 400 m)
10	Number of close intersections	No.close	If Ex_close is 1
11	Number of left-turn moves with turning bay	No.LT_bay	
12	Number of left-turn moves without turning bay	No.LT_nobay	
13	Number of enters in which left-turns do not exist	No.noLT	
14	Number of right-turn moves with turning bay	No.RT_bay	
15	Number of right-turn moves without turning bay	No.RT_nobay	
16	Number of enters in which right-turns do not exist	No.noRT	
17	Number of legs with median (central refuge)	No.Med	
18	Number of legs without median (central refuge)	No.noMed	
19	Total number of enter lanes	No.EntLanes	
20	Total number of exit lanes	No.ExtLanes	
21	Average number of lanes per leg	Lane/Leg	
22	Difference between the numbers of enter and exit lanes	Ent-Ext_lanes	No of enter lanes minus no of exit lanes
23	Existance of close bus stops at enter flows	BusStop_Ent	1:yes, 0: no (closer than 75 m) (HCM 2010)
24	Average distance of close bus stops at enter flows	Dist_BS_Ent	If BusStop is 1
25	Number of close bus stops at left turns of exit flows	No.BS_Ext_LT	
26	Number of close bus stops at through passing exit flows	No.BS_Ext_Str	
27	Number of close bus stops at right turns of exit flows	No.BS_Ext_RT	
28	Average distance of close bus stops at left turns of exit flows	Dist_BS_Ext_LT	If No.BS_Ext_LT is at least 1
29	Average distance of close bus stops at through passing exit flows	Dist_BS_Ext_Str	No.BS_Ext_Str is at least 1
30	Average distance of close bus stops at right turns of exit flows	Dist_BS_Ext_RT	No.BS_Ext_RT is at least 1
31	Average lane width	LaneWidth	(m)
32	Roundabout diameter	RA_dia	If the intersection is roundabout (m)
33	Cycling lane number	RA_no.lane	If the intersection is roundabout
34	Average width of approach median	RA_appr	If the intersection is roundabout (m)
35	Average green time for through passing flow*	GT_Thr	(sec)
36	Average green time for right turn flow*	GT_RT	(sec)
37	Average green time for left turn flow*	GT_LT	(sec)
38	Average green to cycle ratio for through passing flow*	G/C_Thr	
39	Average green to cycle ratio for right turn flow*	G/C_RT	
40	Average green to cycle ratio for left turn flow*	G/C_LT	
41	Average saturated flow of enter legs*	Sat.Flow	(veh./hour)
42	Entering passenger car volume	Vpc	(veh./hour)
43	Entering heavy vehicle volume	Vhv	(veh./hour)
44	Entering total volume	Vtot	(veh./hour)
45	Heavy vehicle ratio	HVR	
46	Entering passenger car volume per lane	VperLpc	
47	Entering heavy vehicle volume per lane	VperLhv	
48	Entering total volume per lane	VperLtot	
49	Average of leg based heavy vehicle ratio	HVRleg	
50	Average of leg based saturation ratios	SatRat	
51	Through passing passenger car volume	Vpc_Thr	(veh./hour)
52	Through passing heavy vehicle volume	Vhv_Thr	(veh./hour)
53	Through passing passenger car equivalent (PCE) volume	Vpce_Thr	(pce/hour)
54	Number of through passing flows	No.Thr	
55	Ratio of through passing flow number to enter flow number	no.Rat_Thr	

** For signalized intersections*

Table 1b - List of explanatory (56-75) and dependent (P1-P8) variables examined in MARS models.

No	Variable Name	Short Name	Description
56	Average ratio of through passing over entering flow	AvRat_Thr	
57	Leg based average ratio of through passing over entering flow	AvRat_Leg_Thr	
58	Right turn passenger car volume	Vpc_RT	(veh./hour)
59	Right turn heavy vehicle volume	Vhv_RT	(veh./hour)
60	Right turn PCE volume	Vpce_RT	(pce/hour)
61	Number of right turn flows	No.RT	
62	Ratio of right turn flow number to enter flow number	no.Rat_RT	
63	Average ratio of right turn over entering flow	AvRat_RT	
64	Leg based average ratio of right turn over entering flow	AvRat_Leg_RT	
65	Left turn passenger car volume	Vpc_LT	(veh./hour)
66	Left turn heavy vehicle volume	Vhv_LT	(veh./hour)
67	Left turn PCE volume	Vpce_LT	(pce/hour)
68	Number of left turn flows	No.LT	
69	Ratio of left turn flow number to enter flow number	no.Rat_LT	
70	Average ratio of left turn over entering flow	AvRat_LT	
71	Leg based average ratio of left turn over entering flow	AvRat_Leg_LT	
72	Entering PCE volume	Vpce	(pce/hour)
73	Average green time per entering vehicle for through passing flow*	GTr_Thr	(sec/(pce/hour))
74	Average green time per entering vehicle for right turn flow*	GTr_RT	(sec/(pce/hour))
75	Average green time per entering vehicle for left turn flow*	GTr_LT	(sec/(pce/hour))
P1	Average delay time per vehicle	P1.DelpVeh	(sec)
P2	Average speed	P2.AvSpeed	(km/h)
P3	Total delay time	P3.TotDelay	(hour)
P4	Total distance traveled	P4.TotDist	(km)
P5	Number of stops	P5.No.Stops	
P6	Number of vehicles that have left the network	P6.No.VehLeft	
P7	Total travel time	P7.Tot_TrlTime	(hour)
P8	Average travel time per vehicle	P8.Ave_TrlTime	(hour/veh.)

* *For signalized intersections*

$$y = b_o + \sum_{m=1}^{M} b_m B_m(x) \qquad (1)$$

where y is the dependent variable; x is the explanatory variable; b_o and b_m are the estimated coefficients to yield the best fit of data; M is the number of basis functions included into the model. $B_m(x)$ is the m^{th} basis function, which can be either a single function or the product of two or more functions for different explanatory variables [34, 46]. The piecewise-linear form of the basis function is shown below:

$$B_m(x) = \prod_{k=1}^{k_m} \left[S_{km} \left(X_{v(k,m)} - t_{k,m} \right) \right] \qquad (2)$$

In the equation, *km* is the number of knots, S_{km} can be either 1 or -1 to indicate the right/left regions of the associated step function, $v(k,m)$ is the label of the explanatory variable, and $t_{k,m}$ is the knot location [34]. A cubic version of this piecewise-linear form also exists for the basis functions, in which a power function is applied for each multiplication segment. However, the piecewise-linear form is preferred in this study to provide simple interpretability.

In the modeling process, two primary steps are applied. The first step is the "construction where basis functions are added to the model using a forward stepwise procedure." The predictors and their knot locations (thresholds) that contribute to the model are defined. In the second step, or the "pruning phase," the basis functions with the least contribution are eliminated using backward deletion. To avoid overfitting, a generalized cross-validation statistic is typically used, where a penalty for model complexity is accounted for [42]. The Generalized Cross-Validation (GCV) criterion is estimated using the following equation:

$$GCV(M) = \frac{1}{N} \frac{\sum_{i=1}^{N} (y_i - \hat{y})^2}{(1 - C\left(\tilde{M}\right) / N)^2} \tag{3}$$

where N is the number of observations; y_i is the response for observation i; $\hat{y}$ is the predicted response for observation i; $C(\tilde{M})$ is the complexity penalty factor.

Step 3; obtains the process for paradigms and strategies. It consists of the generation of design parameters. In this section, the relationship between intersection characteristics and intersection performance results is determined. To obtain the most effective intersection properties that should be considered as the top priority, explanatory variables are analyzed in terms of occurrence frequency and relative importance in the MARS predictions of intersection performance indicators.

Because of the mentioned relationship, the intersection characteristics to be evaluated during the scenario production phase and the intersection characteristics that are meaningful in the model are determined. Hence, the theory of the proposition to be developed has been determined. The most related variables in terms of performance indicators have been chosen to be utilized in the determination process.

Step 4; consists of the generation of design proposals and design verification. At this stage, the design parameters obtained are evaluated and the intervening intersections and method of intervention are determined. The strategies for the selected intersection are determined and a scenario is generated using the determined parameters. The intersection design is generated towards the scenario, and the mentioned intersection design is simulated with the equal traffic demand. Subsequently, the intersection performance indicators are obtained for the designed case, and the intersection design parameters are determined by comparing with the base case intersection performance indicators.

2.2. Study Area

Tekirdağ is a metropolitan seaport that attracts attention oflarge organized industrial zones. The city has significant tourism investments and several advantages due to its location. Tekirdağ is near Istanbul and it is one of the most notable cities in the Marmara region [47]. Tekirdağ has 11 counties, and the most important ones are Süleymanpaşa, Çorlu, and Çerkezköy in terms of economy andpopulation. Çorlu and Çerkezköy lead the industrial sector, while Süleymanpaşa leads the service sector.

The macroform of Süleymanpaşa is adjacent to the seaside. It has a linear urban development between the East–West axis. A belt highway in the north of the city is located as an artificial threshold. The population of the county is 176,848. Çorlu is the largest county of Tekirdağ, and it is 38 km away from the city center. It is one of Turkey's largest counties. Rapid urbanization, intense industrialization, and outside-in migration are the significant problems of the county. The population of the county is 273,362, and it is at the intersection point of large-scaled transportation corridors. Çerkezköy has an increasing population, and it has the highest population density. Many access opportunities to the city exist in terms of transportation modes. The county containing industrial zones has a population of 146,319. Malkara is another significant settlement and it has four intersections with traffic surveys. Locations of four counties are given in Fig. 2.

Traffic surveys and counts are conducted by drones and subsequently counted in the office environment. Counts are conducted for evening and morning peak hours. However, in the study only the morning peak hour count results are evaluated. Traffic counts were performed when the schools were open, and the actual traffic pattern was observed. Counts are conducted in categories such as cars, minibuses, trucks, and buses. The speed and behavior patterns are also observed. The traffic characteristics of the settlements in Tekirdağ are similar to each other. In fact, they are similar to the traffic characteristics of the other medium-sized cities of Turkey. Heavy vehicle traffic and urban public transport traffic constitute only a fraction of the overall traffic. Private car use is relatively high in the overall traffic. Traffic congestion is observed at peak hours in specific central regions. The transportation infrastructure shows that the city is located at the seashore, and some traffic axes are not accessible.

3. ANALYSIS

3.1. Indexing of intersection properties

Traffic surveys and simulations are conducted for 64 intersections. The simulations have been conducted using the VISSIM traffic software. In the calibration section, the vehicle speed and behavior pattern are iteratively updated until the number of vehicles passing through the intersection arms are equalized to the traffic counts. The obtained performance results are generated by a network performance analysis and supported by visual captures. Performance indicators are calculated for the base case. More than 75% of these intersections are located in four sites (Çerkezköy, Çorlu, Malkara, and Süleymanpaşa). Others are scattered in different districts and on intercity roads, including roundabouts, and intersections with signalized and unsignalized intersections. Fig. 3 shows the locations of the intersections in Çerkezköy, Çorlu, Malkara, and Süleymanpaşa.

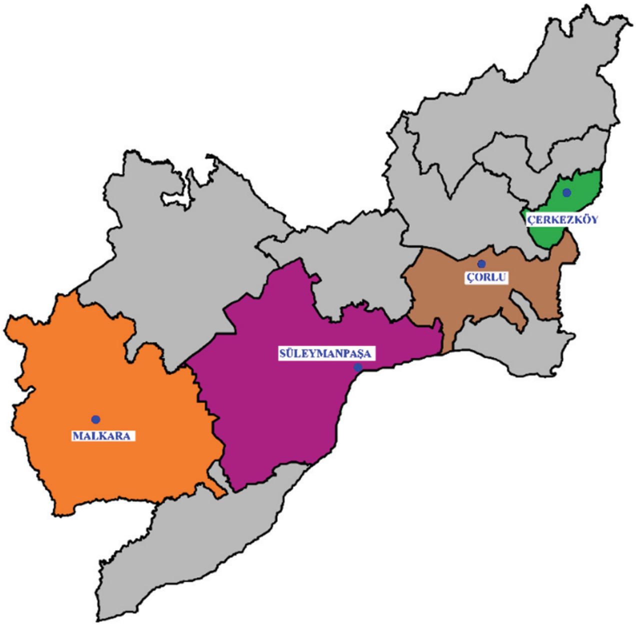

Fig. 2 - Locations of Çerkezköy, Çorlu, Malkara, and Süleymanpaşa

Fig. 3 - Locations of intersections in Çerkezköy, Çorlu, Malkara, and Süleymanpaşa

In this study, we performed a calibration process based on field volumes and number of vehicles that have left the network through 64 intersections. Comparison of field and simulation volumes are given in Fig. 4. As can be seen in the figure, R-squared value is about 0.89 which represents smaller differences between the field data and the fitted values.

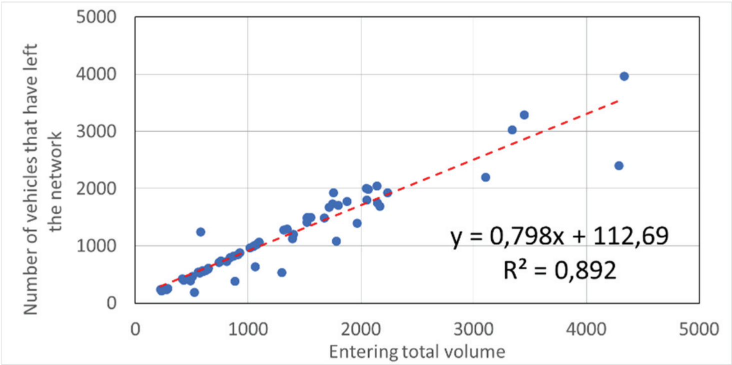

Fig. 4 - Comparison of field and simulation volumes

3.2. MARS model results

The derived intersection characteristics based on geometry, control, and traffic, are examined to estimate eight different intersection performance indicators using the MARS method. In MARS modeling, the functions developed by Jekabsons [48] based on Friedman's method [39, 40] in Matlab programming language are utilized with some modifications according to the scope of the study.

As the first step, data standardization process is added to generated codes. Before performing a MARS model, it is recommended to pre-scale the explanatory and dependent variables to the 0–1 interval [39]. Hence, the transformation equation used is shown below:

$$X_i^s = (X_i^o - X_{\min}^o)/(X_{\max}^o - X_{\min}^o) \tag{4}$$

where X_i^s is the standardized value of the i^{th} observation of the explanatory variable, X_i^o is the observed value, and X_{min}^o and X_{max}^o are the minimum and maximum values of the related observations, respectively.

For the second step of the code modification, basic functions of Jekabsons [48] are combined to construct, converge and evaluate MARS models. The three main steps used in the modeling process are creating structure of model configuration parameters, building MARS model with dependent and independent variables, performing ANOVA decomposition and variable importance assessment. Also a conditional loop is constructed for repeating the process until obtaining a model with significant dependent variables by comparing relative importance values. The relative importance of a variable is defined as the square root of the GCV of the model with all basis functions involving that variable removed, minus the square root of the GCV score of the corresponding full model, scaled such that the relative importance of the most important variable has a value of 100 [35, 40].

In the initial modeling stage, the maximum number of basis functions is limited to 20 in the piecewise linear form, and all of the 75 explanatory variables (intersection characteristics) are included. After the first convergence of the MARS model, the explanatory variables with relative importance smaller than 5% are eliminated, and the model is converged again. This process is repeated until all of the remaining explanatory variables have a relative importance of over 5%.

For clarifying the estimation capability of the models, in addition to the MARS model specific indicators (GCV, R^2_{GCV}), the calculation of some well-accepted statistics that are based on the prediction residuals and widely used for comparing the performance in nonlinear predictions are attached to Jekabsons' functions [48]: root mean square error (RMSE), efficiency factor (EF), post regression statistics for observed and predicted values (slope (m), intercept (b), and coefficient of correlation (r)), and discrepancy ratio percentages (DRP) [49]. DR percentages are provided for both the 10% and 25% discrepancies (see Table 2). Besides, the predictive power of the models are examined by using training and testing stages. For this purpose, randomly selected 42 of 64 intersection data are implemented for training and the generated models are tested by using the remaining 22 intersection data.

As shown in Table 2, all the intersection performance indicators have been considerably predicted by the explanatory variables. All of the models exhibit R^2_{GCV} values over 0.80, and efficiency factors over 0.85. Generally, the MARS model appears to be useful in the estimation of any intersection performance according to the all data-based trainings. The most distinctive differences between the prediction capabilities are obtained by comparing the post regression and discrepancy statistics. When the discrepancy is considered as 25% for all data models, the average speed is shown to be estimated properly for all of the observations. The number of vehicles that have left the network, average travel time per vehicle, total distance travelled, and total travel time also indicate high proper estimation percentages, while the others present considerable percentages for high predictions. When the post regression statistics are compared, the prominent performances can be found as the average speed, total delay time, number of stops, and total travel time, in which the coefficient of correlation (r) is approximately 0.98.

Although convergence performances are increased with randomly divided data, prediction performances with testing set are generally decreased (compared with all data) as expected. According to F-test probability values which should be smaller than 0.05 for a significant performance, average speed (P2), total delay time (P3), number of stops (P5) number of vehicles that have left the network (P6) and average travel time per vehicle (P8) models have high predictive power with testing data. These models still have coefficient of determination (R-squared) and efficiency factors over 0.65. Consequently, it can be said that MARS modeling approach shows prominent estimation capability for these five performance indicators.

According to R^2_{GCV} statistics which is the main indicator of MARS modeling, the performance indicators average speed (P2), number of stops (P5) and total travel time (P7) are found to be the most predictable indicators. Since total travel time is strongly related with the number of vehicles using the intersections, it is preferred to focus on average travel time per vehicle (P8). Consequently, for the brevity of the study, three of the indicators were selected for the comprehensive analysis: average speed (P2), number of stops (P5), and average travel time per vehicle (P8).

Table 2 - General prediction performances of MARS models for eight different intersection performance indicators

Intersection Performance Indicator											
		No:		P1	P2	P3	P4	P5	P6	P7	P8
		Descpriction:		Average delay time per vehicle	Average speed	Total delay time	Total distance traveled	Number of stops	Number of vehicles that have left the network	Total travel time	Average travel time per vehicle
		Short name:		DelpVeh	AvSpeed	TotDelay	TotDist	No.Stops	No.VehLeft	Tot_TrlTime	Ave_TrlTime
MARS model convergence	*all data (64 intersections)*	GCV	:	0.01001	0.00819	0.00586	0.00819	0.00693	0.00346	0.00326	0.00780
		R^2_{GCV}	:	0.880	0.924	0.914	0.789	0.924	0.919	0.935	0.819
	training data (42 intersections)	GCV		0.00349	0.00665	0.00556	0.00600	0.00491	0.00178	0.00176	0.00667
		R^2_{GCV}		0.949	0.930	0.904	0.860	0.938	0.960	0.961	0.828
	Number of basis functions		:	11	9	11	8	11	4	10	10
General prediction performances	*all data (64 intersections)*	R	:	0.972	0.979	0.980	0.934	0.982	0.966	0.983	0.953
		R-squared	:	0.944	0.958	0.960	0.872	0.964	0.934	0.967	0.908
		F	:	89.467	155.436	126.632	54.610	143.531	281.214	173.723	59.032
		Pf	:	0	0	0	0	0	0	0	0
		RMSE	:	0.067	0.066	0.051	0.069	0.056	0.052	0.040	0.062
		EF	:	0.944	0.958	0.960	0.872	0.964	0.934	0.967	0.908
	testing data (22 intersections)	R	:	0.702	0.865	0.803	0.581	0.894	0.830	0.703	0.834
		R-squared	:	0.493	0.747	0.645	0.337	0.800	0.688	0.494	0.695
		F	:	1.582	9.467	5.807	3.053	6.498	5.525	1.074	13.673
		Pf	:	0.22188	0.00024	0.00304	0.05507	0.00164	0.00338	0.45126	0.00007
		RMSE	:	0.230	0.176	0.170	0.144	0.144	0.110	0.168	0.140
		EF	:	0.493	0.747	0.645	0.337	0.800	0.688	0.494	0.695
Post regression statistics	*all data (64 intersections)*	m	:	0.944	0.958	0.960	0.872	0.964	0.934	0.967	0.908
		b	:	0.013	0.024	0.007	0.025	0.008	0.017	0.006	0.027
		r	:	0.972	0.979	0.980	0.934	0.982	0.966	0.983	0.953
	testing data (22 intersections)	m	:	0.579	0.780	1.046	1.099	0.995	1.277	1.212	0.515
		b	:	0.038	0.176	-0.004	0.014	0.007	-0.042	-0.003	0.105
		r	:	0.754	0.885	0.870	0.814	0.912	0.943	0.881	0.930
Discrepancy ratio percentages (10% discrepancy)	*all data (64 intersections)*	DRP_{low}	:	14.06	3.13	15.63	21.88	14.06	1.56	25.00	14.06
		DRP_{proper}	:	37.50	87.50	37.50	42.19	35.94	89.06	45.31	70.31
		DRP_{high}	:	48.44	9.38	46.88	35.94	50.00	9.38	29.69	15.63
	testing data (22 intersections)	DRP_{low}	:	72.73	13.64	22.73	36.36	9.09	22.73	45.45	27.27
		DRP_{proper}	:	9.09	50.00	13.64	9.09	27.27	50.00	9.09	45.45
		DRP_{high}	:	18.18	36.36	63.64	54.55	63.64	27.27	45.45	27.27
Discrepancy ratio percentages (25% discrepancy)	*all data (64 intersections)*	DRP_{low}	:	9.38	0.00	10.94	4.69	4.69	1.56	14.06	4.69
		DRP_{proper}	:	51.56	100.00	48.44	87.50	56.25	93.75	76.56	92.19
		DRP_{high}	:	39.06	0.00	40.63	7.81	39.06	4.69	9.38	3.13
	testing data (22 intersections)	DRP_{low}	:	59.09	0.00	4.55	13.64	4.55	0.00	22.73	4.55
		DRP_{proper}	:	31.82	86.36	59.09	59.09	45.45	100.00	50.00	90.91
		DRP_{high}	:	9.09	13.64	36.36	27.27	50.00	0.00	27.27	4.55

3.2.1. Average Speed (P2)

A high average speed at an intersection can indicate that queuing and delays are at the minimum, and traffic flows without any considerable interruptions. In the MARS models, the average speed provides a successive estimation of the intersection performance. The model converges with 0.00819 GCV value, and nine basis functions (including intercept). Equation 5 shows the final form of the MARS estimation function. The standardized forms of the basis functions are also shown in Table 3. As shown in the equation, the number of phases (No.phases), cycle time (Cyc), entering heavy vehicle volume (Vhv), and entering total volume per lane (VperLtot) are the effective variables in the prediction. According to Eq. 5, No.phases in the MARS prediction indicates that if the number of phases is under four, it increases the average speed by 1.32 km/h for every decreasing number. The critical threshold for Vhv is found to be 714.6 and this variable has two different basis functions. Each additional heavy vehicle over this threshold decreases its average speed by 0.579 km/h, and each vehicle decreasing under this rate also increases by 0.479 km/h. This means that the number of heavy vehicles influences significantly on the average speed. Cycle time values of under 88.956 s present an adverse effect with a -0.775 coefficient. The VperLtot variable has a more complicated effect on the average speed than the other explanatory variables, because of four different basis functions and several threshold values. It can be inferred that a VperLtot of over 151.715 negatively affects the average speed, while it can increase it for values under 138.275 veh/h/lane. A sensitivity analysis, which will be discussed in the next paragraphs, can be more expressive for this type of variables.

$$\begin{aligned}
&\text{P2.AvSpeed} = 31.556 + 1.32*\max(0, 4 - \text{No.phases}) - 0.579*\max(0, \text{Vhv} - 714.6) \\
&+ 0.479*\max(0, 714.6 - \text{Vhv}) - 2.09*\max(0, 310.615 - \text{VperLtot}) \\
&- 0.775*\max(0, 88.956 - \text{Cyc}) + 2.23*\max(0, \text{VperLtot} - 238.675) \\
&- 2.98*\max(0, \text{VperLtot} - 151.715) + 1.99*\max(0, 138.275 - \text{VperLtot})
\end{aligned} \tag{5}$$

Table 3 - Basis function coefficient statistics of MARS model for P2.AvSpeed

No	Basis function	Coefficient	Standard error	t statistics	P-value
BF0	Intercept	0.586	0.118	4.950	0
BF1	max(0, 0.8 - No.phases)	1.324	0.152	8.710	0
BF2	max(0, Vhv - 0.636)	-0.579	0.204	-2.833	0.0064
BF3	max(0, 0.636 - Vhv)	0.479	0.092	5.190	0
BF4	max(0, 0.337 - VperLtot)	-2.094	0.480	-4.367	0.0001
BF5	max(0, 0.706 - Cyc)	-0.775	0.164	-4.733	0
BF6	max(0, VperLtot - 0.246)	2.234	0.790	2.829	0.0065
BF7	max(0, VperLtot - 0.136)	-2.981	0.830	-3.592	0.0007
BF8	max(0, 0.119 - VperLtot)	1.993	0.627	3.178	0.0024

The relative importance of the variables in the model is shown in Table 4. The R^2_{GCV} values in the table show the prediction capability of the MARS model for the case of excluding the considered variable. It is clear that the most important variable in the model is the number of phases. The entering heavy vehicle volume follows this variable. Because limiting the number of heavy vehicles using an intersection is only possible with transportation network management, the number of phases may be considered for maintaining average speed performance.

The relative importance of each basis function in the model can be investigated using Table 3. Considerably small and zero values of probabilities (P) of the t statistics show that every basis function is essential in the prediction of the average speed. When the absolute values of t statistics are compared, BF1 that included No.phases appears to be the most effective basis function. BF3, the intercept, and BF5 follow BF1.

Table 4 - MARS model ANOVA for P2.AvSpeed model.

ANOVA function	Basis functions numbers	Variables	Standard deviation	GCV	R^2_{GCV}	Relative importance
1	5	Cyc	0.25596	0.01061	0.901	28.75
2	1	No.phases	0.47400	0.01793	0.833	100.00
3	2, 3	Vhv	0.11558	0.01344	0.875	58.60
4	4, 6, 7, 8	VperLtot	0.07731	0.01211	0.887	45.04

Fig. 5 demonstrates a graphical sensitivity analysis of the average speed model. For obtaining each line of the figure, the model is simulated 401 times with a range of each considered model parameter between -2 and 2 times of its mean value of observations with 0.01 increment. At every 401 simulations of the considered parameter, the other model parameters are fixed at their mean observation values. Consequently, the corresponding proportional change in model predictions with respect to the model in which all of the model parameters are taken as mean are obtained. The horizontal axis shows the proportional change in each model parameter around the average of observations and the vertical axis indicates the corresponding proportional change in the average speed model. The complicated effect of VperLtot is clearer from the figure. The changes in slopes of the VperLtot line indicates several thresholds in the model. In general, this variable exhibits the largest adverse effect on the average speed performance, when its steepest average slope is considered. While a low Vhv increases the average speed as much as VperLtot, this cannot be assumed for high Vhv. Although the number of phases is the most important variable in the model, the sensitivity graph demonstrates a lower impact than the ones of VperLtot and Vhv. Additionally, the effect of No.phases diminishes over (approximately) a 0.4 increase. The cycle time also decreases the average speed for low ratios (according to the mean of observations); however, it is ineffective for high ratios. It is noteworthy that the sensitivity lines are related to the magnitude and sign of the explanatory variable coefficients. The coefficients may or may not relate to the significance of the explanatory variable in explaining the variance of the dependent variable.

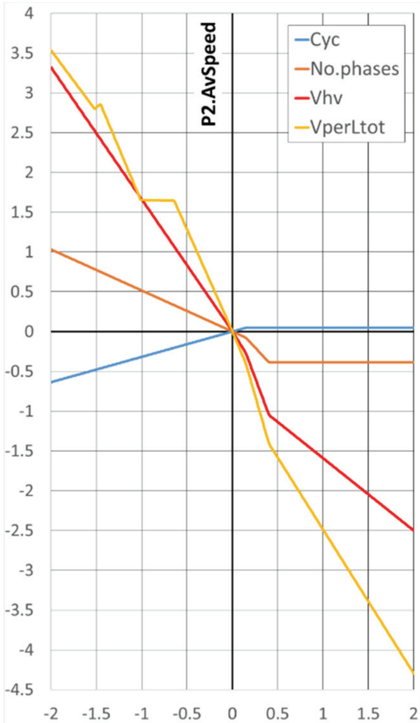

Fig. 5 - Sensitivity analysis for MARS variables in P2.AvSpeed model.

3.2.2. Number of Stops (P5)

The number of stops can be used as a measure of interruptions in traffic flows. The less number of stops means more fluent flows at the intersections. The MARS model of number of stops converges with 0.00693 GCV and 11 basis functions. The final form of the basis functions and their standardized version are shown in Eq. 6 and Table 5, respectively. Seven different parameters are found to be significant in the prediction: average width of approach median of roundabout (RA_appr), entering heavy vehicle volume (Vhv), through passing passenger car equivalent volume (Vpce_Thr), leg-based average ratio of right turn over entering flow (AvRat_Leg_RT), left turning passenger car volume (Vpc_LT), entering passenger car equivalent volume (Vpce), and average green time per entering vehicle for right turn flow (GTr_RT). It can be inferred that the estimation of P5 is rather complicated and related with several parameters depending on vehicle movements, signalization and geometry. Vpce of over 1030 (approximately), and Vhv of over 296 appear to increase the number of stops as threshold values. Additionally, vehicle movements such as Vpc_LT of under 290, and Vpce_Thr of under 410 cause a decreasing effect on this performance. Further, 14% is found to be the threshold for the right turn ratio with two basis functions. Unlike other variables, the roundabout approach width has a linear effect with 0.242 coefficient, implying that this width raises the number of stops in all conditions. Additionally, the average green time per right turning vehicle of over 0.679 s increases the stops.

$$\begin{aligned}P5.No.Stops &= 516.817 + 0.71*\max(0, Vpce - 1029.735) + 0.217*\max(0, GTr\_RT - 0.679) - 0.98*\max(0, 290.241 - Vpc\_LT) + 0.242*\max(0, RA\_appr + 0)\\ &+ 0.294*\max(0, Vhv - 295.5) + 0.21*\max(0, AvRat\_Leg\_RT - 0.139)\\ &+ 0.637*\max(0, 0.139 - AvRat\_Leg\_RT) - 2.07*\max(0, 410.142 - Vpce\_Thr)\\ &+ 1.93*\max(0, 1252.237 - Vpce) - 0.492*\max(0, 448.4 - Vhv)\end{aligned} \tag{6}$$

Table 5 shows that the basis functions including Vpce, Vpc_LT, and RA_appr variables are the most effective basis functions according to the t statistics. Table 6 that includes the relative importance of each variable also shows similar results in the variable-based form. Although Vpc_LT includes only one basis function, it is the second important variable in the MARS model, and this proves the critical significance of left turns in the intersection performance. Fig. 6 demonstrates the sensitivity of the model for each variable, while the others are maintained in their average values. Interestingly, Vpce and GTr_RT show similar sensitivities. This may arise from the site-specific observation correlations of these parameters. Contrary to the regression model, the MARS model does not require multicollinearity analysis and thus the elimination of this type of correlations is simply a modeller preference. Some fluctuations are observed on the sensitivity for the low values of the AvRat_Leg_RT, Vpce, and GTr_RT variables. The emergence of these nonlinear differences is an important advantage of the MARS modeling approach. Although RA_appr is found to be the third most important variable according to the ANOVA statistics, it gives the lowest sensitivity when it is compared with the other variables. This may arise from the limited number of roundabouts and the small range of approach width observations.

Table 5 - Basis function coefficient statistics of MARS model for P5.No.Stops

No	Basis function	Coefficient	Standard error	t statistics	P-value
BF0	Intercept	0.101	0.033	3.046	0.0036
BF1	max(0, Vpce - 0.155)	0.711	0.072	9.922	0
BF2	max(0, GTr_RT - 0.143)	0.217	0.045	4.809	0
BF3	max(0, 0.271 - Vpc_LT)	-0.980	0.115	-8.521	0
BF4	max(0, RA_appr + 0)	0.242	0.034	7.156	0
BF5	max(0, Vhv - 0.255)	0.294	0.086	3.418	0.0012
BF6	max(0, AvRat_Leg_RT - 0.227)	0.210	0.052	4.011	0.0002
BF7	max(0, 0.227 - AvRat_Leg_RT)	0.637	0.156	4.083	0.0002
BF8	max(0, 0.0963 - Vpce_Thr)	-2.072	0.502	-4.131	0.0001
BF9	max(0, 0.201 - Vpce)	1.926	0.309	6.241	0
BF10	max(0, 0.394 - Vhv)	-0.492	0.163	-3.030	0.0038

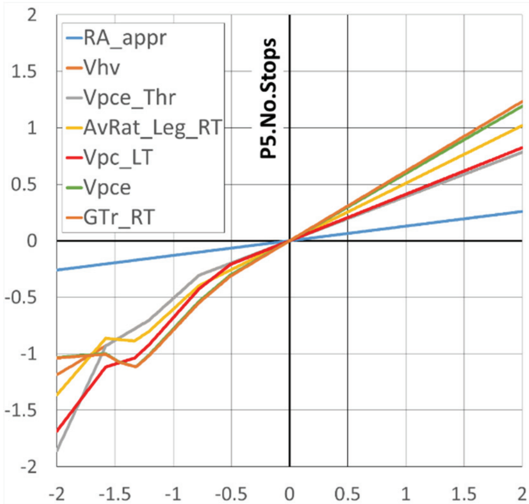

Fig. 6 - Sensitivity analysis for MARS variables in P5.No.Stops model.

Table 6. MARS model ANOVA for P5.No.Stops model.

ANOVA function	Basis functions numbers	Variables	Standard deviation	GCV	R^2_{GCV}	Relative Importance
1	4	RA_appr	0.05983	0.01243	0.863	41.74
2	5, 10	Vhv	0.11046	0.01013	0.888	25.74
3	8	Vpce_Thr	0.04767	0.00836	0.908	12.11
4	6, 7	AvRat_Leg_RT	0.04250	0.00824	0.909	11.11
5	3	Vpc_LT	0.09449	0.01499	0.835	57.85
6	1, 9	Vpce	0.12968	0.02280	0.748	100.00
7	2	GTr_RT	0.04163	0.00908	0.900	17.83

3.2.3. Average Travel Time (P8)

The average travel time per vehicle can be considered as a convenient performance tool that can be an indicator of many intersection characteristics such as dimensions, management, saturation, etc. Although the P8 MARS model is less successful than P7 according to Table 2, it is preferred for examination because of two aspects: the average travel time can reflect the critical intersection performances average speed and delay together, and it is an indicator independent from traffic counts. Additionally, this measure has prominent discrepancy ratio statistics with a high proper percentage and balanced values for low and high percentages. The model adequately converges with 0.0078 GCV and 10 basis functions. The efficient variables on the prediction of the average travel time are found as the average of the leg-based saturation ratios (SatRat), intersection dimensions in the North–South and East–West directions (Dim_NS and Dim_EW), average green-to-cycle ratio for right turn flow

(G/C_RT), left turn passenger car volume (Vpc_LT), difference between the numbers of enter and exit lanes (Ent-Ext_lanes), and through passing heavy vehicle volume (Vhv_Thr). The prediction equation (7) shows the critical thresholds and coefficients of these variables. The standardized forms and statistics of the basis function can also be found in Table 7. The saturation ratio for signalized intersections occurs in two different basis functions with the same threshold, 0.132. Meanwhile, a SatRat smaller than 0.132 decreases the travel time with a -0.17 coefficient, and also decreases it with a -0.33 coefficient for values over this threshold. This may arise from the signalized intersection observations with small saturations in general. The intersection dimensions are measured as the distance between stop lines for the NS and EW bounds. The related basis functions show that if the dimensions are higher than 50 m in the NS bound, it increases the average travel time with a 0.564 coefficient, while Dim_EW decreases it with a -0.26 for distances under 54 m (approximately). The green-to-cycle ratio of over 0.146 for the right turn flow decreases the average travel time with a -0.296 coefficient. The left turn passenger car volume of over 177 increases the travel time with a 1.71 coefficient, and it decreases if it is over 315 with a -1.72 coefficient. If the similar and opposite signs of the coefficients of these basis functions are considered, it can be said that the Vpc_LT effect diminishes for the counts over 315. The average left turn passenger car is 208 for the observed roundabouts; thus, this reduction is shown for some extreme observations.

$$\begin{aligned}\text{P8.Ave\_TrlTime} = {} & 0.041 - 0.33*\max(0, \text{SatRat} - 0.132) - 1.17*\max(0, 0.132 \\ & - \text{SatRat}) + 0.564*\max(0, \text{Dim\_NS} - 50.032) - 0.296*\max(0, \text{G/C\_RT} - 0.146) \\ & + 1.71*\max(0, \text{Vpc\_LT} - 176.715) - 0.78*\max(0, 0.002 - \text{Ent- Ext\_lanes}) \\ & + 0.494*\max(0, \text{Vhv\_Thr} - 375.25) - 0.26*\max(0, 53.974 - \text{Dim\_EW}) - 1.72*\max(0, \\ & \text{Vpc\_LT} - 314.874)\end{aligned} \tag{7}$$

Table 7 - Basis function coefficient statistics of MARS model for P8.Ave_TrlTime.

No	Basis function	Coefficient	Standard error	t statistics	P-value
BF0	Intercept	0.416	0.026	15.790	0
BF1	max(0, SatRat - 0.171)	-0.331	0.092	-3.579	0.0007
BF2	max(0, 0.171 - SatRat)	-1.169	0.167	-6.989	0
BF3	max(0, Dim_NS - 0.296)	0.564	0.098	5.734	0
BF4	max(0, G/C_RT - 0.143)	-0.296	0.068	-4.376	0.0001
BF5	max(0, Vpc_LT - 0.165)	1.713	0.230	7.450	0
BF6	max(0, 0.286 - Ent-Ext_lanes)	-0.780	0.194	-4.013	0.0002
BF7	max(0, Vhv_Thr - 0.475)	0.494	0.128	3.865	0.0003
BF8	max(0, 0.578 - Dim_EW)	-0.260	0.073	-3.562	0.0008
BF9	max(0, Vpc_LT - 0.294)	-1.716	0.303	-5.662	0

The entering lane number over exit lanes (positive Ent-Ext_lanes) may be observed in improper intersection designs. The related basis function show that it decreases the average travel time if it is negative, as expected. Through passing heavy vehicle volume (Vhv_Thr) is also found to be an increase factor (with a positive 0.494 coefficient) on the travel time for the observations of over 375.

According to the t statistics in Table 7, the most effective basis functions can be sorted as BF5 (Vpc_LT over knot with a positive coefficient), BF2 (SatRat under knot with a negative coefficient), and BF3 (Dim_NS over knot with a positive coefficient). According to the ANOVA analysis of the variables shown in Table 8, Vpc_LT is the most important variable for the average travel time prediction. The R^2_{GCV} value decreases to 0.649 from 0.819 when this variable is excluded. SatRat and Dim_NS follow this variable. It can be inferred that, especially the left turning passenger car volume should be maintained under 176, saturation ratio under 0.132, and intersection dimensions under 50 m for an acceptable travel time performance. It is noteworthy that these threshold values may be case specific, and similar modeling processes should be performed for intersection observations from other countries or cities where the driver behavior may differ under various intersection geometry, traffic composition, and management conditions.

Table 8 - MARS model ANOVA for P8.Ave_TrlTime model.

ANOVA function	Basis functions numbers	Variables	Standard deviation	GCV	R^2_{GCV}	Relative importance
1	8	Dim_EW	0.04426	0.00883	0.795	16.31
2	3	Dim_NS	0.05497	0.01150	0.733	54.65
3	6	Ent-Ext_lanes	0.03579	0.00928	0.785	23.16
4	4	G/C_RT	0.04132	0.00968	0.775	29.14
5	1, 2	SatRat	0.08107	0.01317	0.695	76.30
6	7	Vhv_Thr	0.04051	0.00913	0.788	20.84
7	5, 9	Vpc_LT	0.09253	0.01512	0.649	100.00

A graphical sensitivity analysis of the average travel time model is shown in Fig. 7. Except for the dimensions variables (Dim_NS and Dim_EW), the lower values of all other variables appear to have a higher decreasing effect on the travel time, when it is compared with their increasing effect for higher values (according to the average) because the sensitivity slopes are generally larger at the left side. Therefore, maintaining these variables under some acceptable averages is preferable.

3.3. Selection of Intersection Design Parameter(s)

In this section, the model results are interpreted and new design parameters are generated to modify the existing intersections. An intersection has been selected for modification and a design is generated.

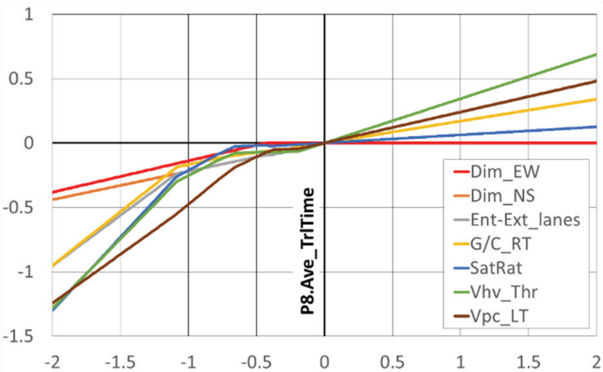

Fig. 7 - Sensitivity analysis for MARS variables in P8.Ave_TrlTime model.

Table 9 - The selected intersection design parameters and performance indicators

	Intersection Performance	***Intersection dimension in North-South direction (Dim_NS)***					***Left turn passenger car equivalent volume (Vpc_LT)***				
		Relative Importance	No of BF	Coef.	t stat.	Basis Function(s) [BF]	Relative Importance	No of BF	Coef.	t stat.	Basis Function(s) [BF]
P1	Average delay time per vehicle	88.26	1	0.715	6.748	max(0, Dim_NS -50.032)	21.62	1	0.368	3.739	max(0, Vpc_LT -117.81)
P2	Average speed	-	-	-	-	-	-	-	-	-	-
P3	Total delay time	43.64	1	0.397	5.073	max(0, Dim_NS -50.032)	-	-	-	-	-
P4	Total distance traveled	-	-	-	-	-	-	-	-	-	-
P5	Number of stops	-	-	-	-	-	57.85	1	-0.98	-8.521	max(0,290.241 -Vpc_LT)
P6	Number of vehicles that have left the network	-	-	-	-	-	-	-	-	-	-
P7	Total travel time	6.22	1	0.26	4.174	max(0, Dim_NS -53.014)	12	3	-2.011 1.151 0.969	-5.246 3.986 3.792	max(0,299.88 -Vpc_LT) max(0,134.946 -Vpc_LT) max(0,404.838 -Vpc_LT)
P8	Average travel time per vehicle	54.64	1	0.564	5.734	max(0, Dim_NS -50.032)	100	2	1.713 -1.716	7.445 -5.662	max(0, Vpc_LT -176.715) max(0, Vpc_LT -314.874)

To obtain the intersection design parameters that should be considered as a first priority, 75 explanatory variables are analyzed in terms of occurrence frequency and relative importance in the MARS predictions of eight different intersection performances. The intersection dimensions (North–South direction) and left turn passenger car volume are found to be the most frequently included parameters in the performance prediction, with inclusion in four different prediction models for both. The model statistics regarding these variables are shown in Table 9. The average delay, and the total and average travel times are typical performance indicators for these intersection features. The "t" statistics of the intersection dimensions are over "4," and the threshold values in the basis function varies between 50–53 m. The dimensions over these threshold values adversely affect many performance indicators with positive coefficients. The influence of the left turning passenger car volume is rather complicated especially for the travel-time-based performances. It occurs with two or more basis functions with several thresholds in the prediction models. For example, according to

Table 9, while a Vpc_LT higher than 118 veh./h increases the average delay per vehicle with a 0.368 coefficient, it decreases the number of stops with a -0.98 coefficient for Vpc_LT values smaller than 290 veh./h. The MARS models reflect many nonlinearities regarding the traffic count dynamics. Meanwhile, improving the traffic volume-based variables is more difficult than improving the geometric variables. This requires the implementation of network management tools such as one-way applications and left-turn constraints. Therefore, the intersection dimensions are chosen as the basic design parameter. It is worth noting that the prominence of intersection dimensions is a case-specific result, and different intersection observations and driver behaviors from another city may cause alternative conclusions. The proposed stepwise paradigm should be followed for each site study to obtain sound results.

3.4. Testing of Intersection Design Parameter

To test the improvement, a traffic simulation for the chosen intersection has been performed for the base case and for the proposed solution. Subsequently, before and after analysis have been conducted to evaluate the improvement.

The chosen intersection to test is called "Narin Kavsağı". It is a signalized roundabout with a diameter of 64 m. The vehicle volumes of the intersection legs are presented in Table 10. The intersection demand in the proposed solution is assigned the same as the base case. Five arms and four routes exist for each intersection arm; therefore, 20 routes are available. The traffic speed values are calibrated by surveys as follows: passenger car, 50 km/h; HGV, 30 km/h; bus, 30 km/h; minibus, 40 km/h.

Table 10 - Vehicle input for the intersection (veh/hour)

Departure leg / Approach leg	A				B				C				D				E			
	Car	HGV	Bus	Minibus	Car	HGV	Bus	Minibus	Car	HGV	Bus	Minibus	Car	HGV	Bus	Minibus	Car	HGV	Bus	Minibus
A	0	0	0	0	20	0	0	5	34	0	0	11	7	0	0	3	6	0	0	4
B	26	1	1	2	0	0	0	0	50	5	6	9	60	7	4	9	0	0	0	0
C	195	15	12	33	10	1	1	3	0	0	0	0	65	7	3	15	70	4	3	8
D	59	4	4	8	48	5	4	13	363	7	8	27	0	0	0	0	330	10	11	29
E	190	0	0	0	135	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Intersection layout, signal groups and phase diagrams for base case and proposed solution are given in Fig. 8. The intersection has been simulated for the base case and subsequently redesigned in terms of dimensions. It has been transformed into an intersection that is narrower and not a roundabout, by following a new intersection design paradigm. The redesigned intersection has also been simulated in the VISSIM traffic simulation software. The visual comparison of the mentioned simulations in the 3000th second is shown in Fig. 9.

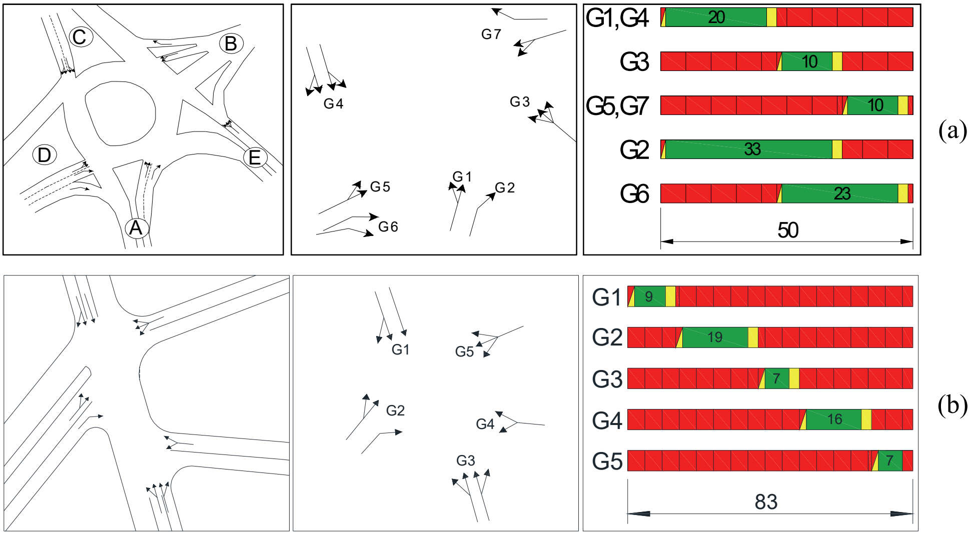

Fig. 8 - Intersection layouts, signal groups and phase diagrams of "Narin" Intersection for base case (a) and for the proposed solution (b)

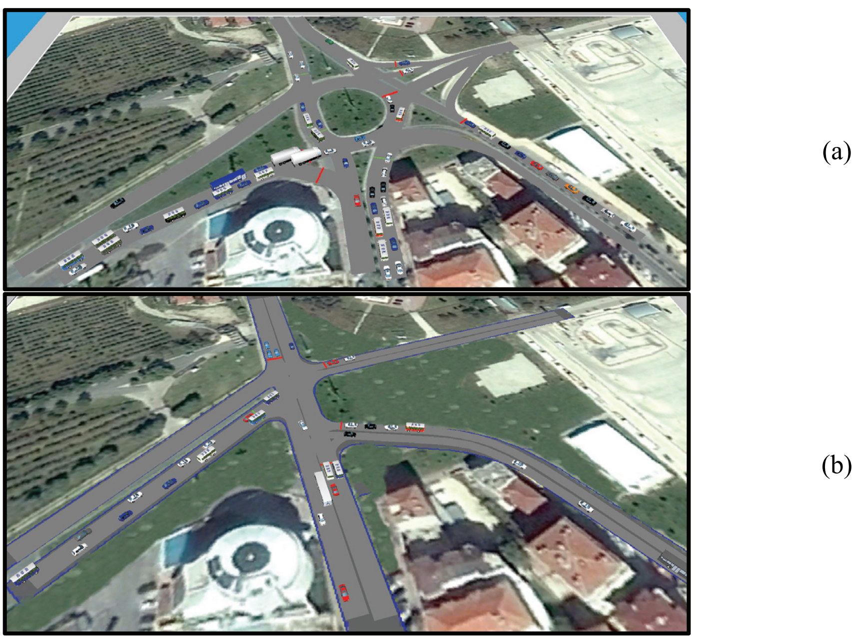

Fig. 9 - The visual comparison of intersection for base case (a) and for the proposed solution (b) (3000th second of the simulation).

As shown in Fig. 9, the dimensions of the intersection have been reduced, and the traffic jam has decreased. The performance indicators for the base case and proposed solution has been compared in Table 11. The performance indicators: average delay time per vehicle, average speed, total delay time, and total distance travelled are the primary correlated indicators with variables. Thus, the improvements on those indicators are validations of the test section. Table 11 shows noteworthy change percentages at performance indicators between 2% and 29%. The increase in the total distance travelled is likely due to the rising number of vehicles that have successfully left the network. Except for that, all the performance indicators were improved. The average speed and number of stops are the most improved performances, i.e., of over 25%. Consequently, using the proposed stepwise analysis, only one critical intervention can significantly improve the crucial intersection performances such as the average delay and speed.

Table 11 - Comparison of intersection performance indicators for base case and proposed solution

	Performance indicators	Base case	Proposed solution	Change
P1	Average delay time per vehicle (s)	45.25	35.93	-20.6%
P2	Average speed (km/h)	10.95	14.11	28.9%
P3	Total delay time (h)	21.67	19.35	-10.7%
P4	Total distance travelled (km)	307.00	386.19	25.8%
P5	Number of stops	2572	1870	-27.3%
P6	Number of vehicles that have left the network	1698	1912	12.6%
P7	Total travel time (h)	28.04	27.36	-2.4%
P8	Average travel time per vehicle (min.)	0.99	0.86	-13.3%

4. CONCLUSIONS

In the study, a stepwise analysis briefly including intersection indexing and microsimulation, MARS-based performance prediction, selection of intersection design parameters, and testing were conducted. It was aimed to provide a holistic strategy for the description of fundamental components that decrease the intersection-based highway network performance. An average of 80 intersections in Tekirdağ were investigated with eight performance indicators. Using the MARS method, which is a promising modeling technique providing nonlinear and parametric estimations, many intersection parameters such as heavy vehicle volume, number of phase, cycle time, total entering vehicle per lane, saturation ratio, and intersection dimensions were found to be critical factors affecting the intersection performance with several threshold values. The variable of intersection dimensions of over 50 m was found to show the most significant effect on the average speed, average delay time per vehicle, total delay time, average delay time per vehicle, and number of stops indicators. According to the obtained result, a new intersection design was created, which was below the 50 m threshold. The intersection design was simulated and compared with the base case situation, and the improvement results were obtained. According to the results obtained, the offered intersection type was more efficient in terms of all the performance indicators, i.e., up to 29%.

Many intersections, intersection characteristics, and performance indicators exist in the model. Therefore, it generated a backdrop for interpretations and subjective perspectives. It is helpful for planners to determine which design parameters to be prioritized, and which intersections should be prioritized. Many options are available for setting the mentioned priorities in the proposed model.

It is meaningful to evaluate the general characteristics of the intersections before intervening in the interchanges. The analytical nature of the assessment performed will provide a more accurate decision-making process. The mentioned model may be utilized in the urban transportation studies of local administrations. It may also be used at the lower stages of transportation planning.

There are several traffic related problems in big cities of both developing and developed countries. As known, most of these problems arise from low performance of the intersections. In such cases, specific intersection redesign proposals may provide improved results in terms of delays and congestion. The model developed in this study reveals the major intersection design parameters, which may be useful to evaluate by the planners and decision-makers in intersection redesign process. For the case area of this study, as it is stated in Table 9, planning process should start with improvements on intersection dimensions (in the north direction) and left turn volumes. The model may be utilized in new planning processes since the data generated by the model provides an essential information for decision makers.

Various policies should be developed before the interventions at crossroads in future work. These intervention policies can be determined by the proposed model or by the evaluation of many different data. Finally, since there are still many other significant variables affecting the intersection performance, the proposed model will be extended considering some other key determinants which can impact on the model.

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