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Interactive allocation of mobile photo enforcement resources with multiple program objectives.

AUTHOR POST PRINT VERSION

1 **ABSTRACT**

2 Managers of mobile photo enforcement (MPE) programs must account for several road safety

3 goals when deploying operators. However, there is no MPE design structure to systematically

4 connect deployment decisions back to preset goals. We propose a method to aid MPE managers in

5 using goals directly in the efficient allocation of limited program resources. A neighborhood-level

6 resource allocation model is developed, which uses multi-objective optimization to determine how

7 enforcement is allocated to city neighborhoods. The model is applied to an MPE program in

8 Edmonton, Alberta, Canada, and delivered 200 optimal solutions for one month. One illustrative

9 solution is plotted in GIS and assessed alongside the actual program deployment results for the

10 same month. This solution efficiently allocates one month of operator shifts to sites in 44

11 neighborhoods, based on the specific needs of each neighborhood. The actual MPE deployment

12 was such that 60% of visits occurred in neighborhoods beyond the 44 identified in the illustrative

13 optimal solution. The major contribution of our model is that it allows for MPE managers to

14 quantitatively map performance outcomes to multiple program goals. This can lead to more

15 transparent and efficient MPE programs, which in turn can improve urban road safety and

16 ultimately, urban sustainability.

17

18 *Keywords*: Mobile photo enforcement, resource allocation, multi-objective linear programming,

19   Geographic Information System

20

21 *Note:* Color should be used for all figures

1.   INTRODUCTION

Roadway traffic collisions impose a serious impact on society, claiming more than one million lives worldwide each year, and this number is increasing (*1*). Saving the lives lost in traffic accidents is an indicator of urban sustainability (*2, 3*); however, traditional government interventions have not been highly effective in slowing or stopping the overall global trend of rising road fatalities. Since 2000, many cities have begun to develop and implement new road safety strategies, notably Vision Zero or Sustainably Safe Road, which aim to eliminate fatality and serious injury collisions (*4, 5*).

Mobile photo enforcement (MPE) programs are documented to be an essential tool for achieving the Vision Zero road safety goal, and therefore play a critical role in promoting the continued sustainable growth of cities. An MPE program deploys operators driving vehicles containing photo radar cameras, which are used to catch speed violators. MPE programs have been effective in reducing fatal collisions by 17%-30% (*6, 7*).

However, decisions on how to allocate operators within an MPE program is a multi-objective problem. Program managers must consider several objectives simutaneouly, such as assigning operators to roadway locations experiencing high collision rates, high speed limit violations rates, and dense pedestrian traffic (*8*). Nonetheless, enforcement resources are usually limited due to the high costs of manpower and equipment.

Randomized resource allocation discussed in (*9–11*) is a significant method for MPE deployment. The method randomly matches enforcement sites with daily operator hours to improve the drivers' perception of randomness of MPE operation. Kim et al. (*11*) further introduces a priority index into this method to consider multiple deployment goals; however, the index values depend on the weights assigned to goals, which are difficult to obtain and are therefore based on program managers' judgment and experience.

1   Very little research has been carried out on how to efficiently allocate finte MPE resources

2   to address its program purposes. In contrast, since the early 1970s many studies have been

3   conducted on how to optimally allocate emergency facilities such as fire stations, police stations,

4   or emergency medical service (EMS) stations (*12–14*). Two typical approaches to solving this

5   problem are the set covering location model (*12*) and maximal covering location model (*13*). The

6   former covers all the demand for emergency services within a maximal service distance, while the

7   latter covers areas with high demands using limited resources. However, most emergency facilities

8   are stationary. Yin (*15*) proposes a min-max optimization model to optimally allocate mobile

9   police patrol vehicles to freeway segments. As the model is developed based on the total patrol

10   travel time spent handling worst-case freeway incidents, the optimal resource allocation plan

11   obtained is independent of time and therefore independent of demand (that changes over time).

12   Adler et al. (*16*) develops a maximal covering location model, allocating freeway police patrol

13   vehicles based on demands that change over time. To consider multiple deployment goals without

14   assuming weights for each, the model employs multi-objective optimization techniques.

15   Although the aims of freeway police patrol programs focus on timely response to calls for

16   service and general road policy duties rather than on identifying speed violators and reducing

17   speeds at various roadway locations, namely the goals of MPE programs, the benefits of the two

18   programs are similar. Hence, we propose an MPE resource allocation model that uses multi-

19   objective optimization to aid MPE managers in directly imposing multiple program goals in the

20   efficient allocation of limited program resources. The model is applied to an MPE program in

21   Edmonton, Canada, using three priorities—high collision sites, high speed violation sites, and

22   school zones—that often receive the most enforcement attention, as reviewed in (*8*). The model

23   assigns monthly operator shifts to city neighborhoods, directing enforcement coverage according

24   to each neighborhood's enforcement demand and needs quantified by three neighborhood-level

1   metrics: equivalent property-damage-only (EPDO) collision frequency per kilometer (km), speed

2   violation indicator (SVI), and school zone density.

3   This paper provides a data-driven process for mapping high-level road safety goals to MPE

4   deployment planning decisions. This process has existed as a "black box" insofar as it has not been

5   explicitly defined in the literature. Our proposed model can greatly facilitate the development and

6   deployment of transparent and efficient speed enforcement programs, which will enhance traffic

7   safety outcomes and more broadly, sustainable urban growth. Application of our model yields a

8   pool of optimal deployment solutions, allowing program managers to consider multiple objectives

9   in deploying MPE program resources. Instead of setting predetermined weights on the objectives,

10 our method allows program managers to choose an optimal solution based on their preferences

11 and needs at a given time. Finally, neighborhood-level deployment plans offer city- or region-wide

12 information regarding where enforcement needs are and how to address them, such that program

13 managers can then schedule individual resources to individual enforcement sites within each

14 neighborhood.

15 2.   **MOBILE PHOTO ENFORCEMENT (MPE) RESOURCE DEPLOYMENT**

16   **FRAMEWORK**

17 The MPE resource deployment framework uses multi-objective optimization to map high-level

18 program goals to deployment decisions. The deployment process can be described in three parts

19 (Fig. 1): defining high-level program goals, the multi-objective linear programming (MOLP)

20 resource allocation model, and choosing the final deployment plan for implementation.
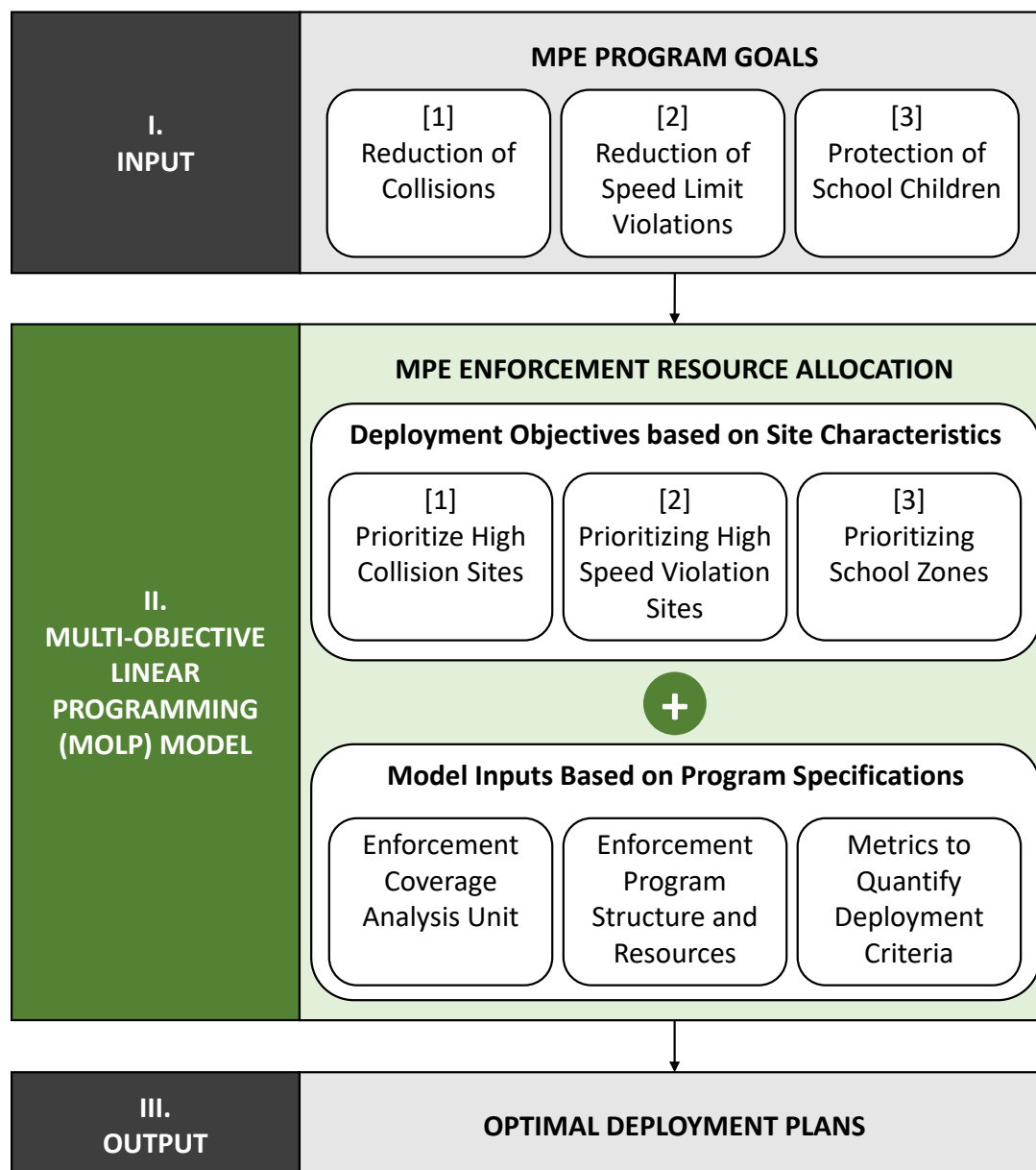
FIGURE 1 MPE deployment framework.

The inputs to the MPE deployment, as shown in Fig. 1, includes the three most critical and frequently considered high-level MPE program goals: reduction of collisions, reduction of speed limit violations, and presence in school zones (*8*). Although any number of, and types of, goals can be considered, the three mentioned above were chosen because of their prominence in the literature (*8*).

1   As discussed in Section 2, limited research has been conducted on how to allocate and

2   utilize MPE program resources with direct consideration for multiple program goals. Therefore,

3   Stage II of Fig. 1 has traditionally been a "black box"—inherently qualitative and imprecisely

4   defined. We propose multi-objective linear programming (MOLP) to connect deployment

5   decisions back to high-level program goals in Stage II, which requires two major tasks. The first

6   is to convert high-level goals into operational deployment objectives. In this research, the

7   operational deployment objectives consist of prioritizing sites with a high rate of collisions, high

8   rate of speed limit violations, and those within school zones. The second task is to identify

9   program-specific characteristics for use in the MOLP allocation model. In this research we have

10   identified three: geographic units for enforcement allocation, program resources (i.e., operators,

11   shift scheduling rules, equipment, etc.), and metrics to quantify the operational deployment

12   objectives in the first task. The details of Stage II are discussed in Sections 3.1 and 3.2. The model

13   outputs a set of candidate deployment options from which program managers can choose, based

14   on their specific preferences and needs at a given time.

15   **2.1   MOLP Model Inputs**

16   Here we discuss the three inputs of the MOLP model as identified in Part II of Fig. 1, as defined

17   for the MPE program in the city of Edmonton (COE), Alberta, Canada. Data was provided by the

18   City of Edmonton Office of Traffic Safety, which oversees the COEs MPE program. Managers of

19   other MPE programs with different operational and geographic considerations may need to adjust

20   these inputs.

21   *2.1.1   Geographic Units for Enforcement Allocation*

22   In the COE, MPE sites are urban mid-block sections, their locations and lengths having been

23   assessed and approved by MPE program managers. The MPE program has a site pool consisting

24   of more than 1000 sites that are candidates for enforcement; with a limited set of operators,

1   vehicles, and equipment, deciding where to send these resources can be difficult. To make the

2   planning stage of this deployment problem tractable, we allocate enforcement resources at a

3   neighborhood level. A neighborhood is the considered unit of study in our application because it

4   is commonly understood, and descriptive data is often available at this level of urban aggregation.

5   In addition, neighborhoods have been proposed in road safety evaluation research to support high-

6   level management (*17*, *18*).

7   *2.1.2   Program Resources*

8   The COEs MPE program is conducted through operator shifts that cover 20 hours of a day, seven

9   days a week. During a shift, an operator is assigned to police speed at a set of enforcement sites.

10   The 20-hour daily enforcement is divided into two shifts, including a daytime shift from 6AM-

11   4PM and an evening shift from 4PM-2AM. Therefore, we quantify available program resources in

12   terms of the total monthly number of shifts. Providing deployment plans that cover a month is

13   preferable to weekly or yearly plans, in order to best utilize historical data and maintain the

14   perception of program randomness (*19*).

15   *2.1.3   Metrics to Quantify Operational Deployment Objectives*

16   We quantitatively define the three neighborhood-level deployment criteria based on those

17   proposed by Li et al. (*8*). First, the total Equivalent property-damage-only (EPDO) collision

18   frequency divided by the total road length (in km) for each neighborhood is used to quantify a

19   neighborhood's need for enforcement with regard to collision rates. Second, a speed violation

20   indicator (SVI) is used to aggregate the proportion of vehicles exceeding the speed limit per

21   neighborhood. SVI is the average of the percentage of violating vehicles across all segments in

22   each neighborhood, weighted by the traffic volume over the length of time measured for each

23   segment (*20*). Third, neighborhood school zone density, computed by dividing the total number of

24   school zones by the total neighborhood area (in sq.km), is used to assess the level of enforcement

1 needed in a neighborhood due to the presence of schools. Neighborhoods exhibiting high metrics

2 warrant a high level of enforcement, and the model is designed to allocate as many shifts as

3 possible to these neighborhoods.

4 **2.2 MOLP Model**

5 A multi-objective linear programming (MOLP) model (Eqns. 1-3) is used to allocate one month

6 of enforcement shifts to city neighborhoods, to optimize the three deployment criteria

7 simultaneously. The three deployment objectives are quantified using the metrics introduced in

8 Section 3.1.3; the higher the total of the three metrics is for a neighborhood, the more enforcement

9 shifts one would expect to be allocated to that neighborhood.

10 Decision Variables:

11 x_i = number of operator shifts assigned to neighborhood i in a given month, $i \in [1, \dots, n]$.

12 Objective Functions:

13 $$max \begin{cases} (I) & \sum_{i=1}^{n} EPK_i \cdot x_i \\ (II) & \sum_{i=1}^{n} SVI_i \cdot x_i \\ (III) & \sum_{i=1}^{n} SZD_i \cdot x_i \end{cases} \qquad (1)$$

14 Subject to

15 $\sum_{i=0}^{n} x_i = P$ $\qquad\qquad (2)$

16 $L_i \leq x_i \leq U_i, \ \forall i$ $\qquad\qquad (3)$

17 where:

18 i = neighborhood index, $i = 1, \dots, n$;

19 EPK_i = EPDO collision frequency per kilometer (km) for neighborhood i;

20 SVI_i = speed violation indicator for neighborhood i;

21 SZD_i = number of school zones per square kilometer (sq.km) for neighborhood i;

22 P = number of total shifts in one month;

23 L_i = minimum allowable shifts that may be allocated to neighborhood i in one month, and

1   U_i = maximum allowable shifts that may be allocated to neighborhood i in one month.

2

3   Eqn. 1 consists of three objective functions, each of which sums the product (over all

4   neighborhoods) of a neighborhood's metric in question and number of shifts assigned to that

5   neighborhood in the one given month. Eqn. 1 maximizes the three objective functions

6   simultaneously, with respect to the constraints on the total number of shifts available in one month,

7   P (Eqn. 2), and the minimum and maximum shifts allowed for each neighborhood over that month,

8   L_i and U_i (Eqn. 3). The model searches for the optimal shift distributions to neighborhoods $[1 \ldots n]$,

9   allocating as many shifts as allowed by Eqn. 3 to neighborhoods experiencing high EPK_i, SVI_i,

10   and SZD_i.

11   **3.**   **APPLICATION AND RESULTS**

12   The model described in Section 3 was applied to produce candidate deployment plans for the COEs

13   MPE program in September 2014. September was chosen because it is known that the COE MPE

14   program aims to dedicate greater enforcement efforts to school zones at this time of year. We used

15   GIS mapping to present one deployment plan produced by the MOLP model, which assigned

16   higher priority to school zones and less to high collision and speed violation sites. Furthermore,

17   these deployment results were visually compared against the results of the actual September 2014

18   MPE program deployment.

19   **3.1**   **Description of the Data**

20   This section describes the data collected from the Edmonton case study. Data used for input to the

21   MOLP model, including the metrics used for the objectives and total MPE program resources for

22   a given month, are described.

23   The COE has $n = 388$ neighborhoods. Three years (2012-2014) of geocoded data

24   consisting of 18,198 speed-related midblock collisions, 893 speed survey reports, and 296 schools'

1   information were assigned to their corresponding neighborhoods in GIS, to calculate the three

2   neighborhood-level metrics introduced in Section 3.1.3 and Eqn. 1. It is noted that in computing

3   EPDO collision frequency, the direct cost of collisions of different severity levels, were used as

4   the weights for different collision severities. Specifically, according to this 2010 report (*21*), one

5   fatal collision is equivalent to 16.6 PDO collisions and one injury collision is equivalent to 3.6

6   PDO collisions. Of the 388 COE neighborhoods, most neighborhoods have EPDO/km values

7   between 0 and 7.7 EPDO/km, speed violation indicator (SVI) values between 0 and 0.6, and school

8   zone densities (school zones/sq.km) between 0 and 1.6, from 2012-2014.

9   Fig. 2 illustrates the neighborhoods that have calculated metrics within the top 10% of each

10   of the three criteria; these neighborhoods are those that we have defined as warranting high

11   enforcement attention.

Neighborhood Metrics (3-Year Average)

		Number of Neighbor-hoods	EPDO/km	SVI	School Zone Density (sq.km)
Neighbor-hoods within Top 10% of Metrics	Any Two of Three Metrics	9	11.1	0.7	0.3
	Exclusively EPDO/km	32	11.9	0.3	0.4
	Exclusively SVI	31	3.1	0.8	0.3
	Exclusively School Zone Density	36	4.5	0.4	2.7
Total Neighborhoods		388	4.3	0.3	0.7

Neighorhoods by Metrics, 2012-2014

- Neighborhoods within Top 10% of Any Two of Three Metrics
- Neighborhoods Exclusively within Top 10% of EPDO/km
- Neighborhoods Exclusively within Top 10% of SVI
- Neighborhoods Exclusively within Top 10% of School Zone Density
- Neighborhoods not within Top 10% of Any Metric
- Road Network

FIGURE 2 Edmonton neighborhoods ranked by criteria, 2012-2014.

1 As seen in Fig. 2, there are no neighborhoods that fall in the top 10% of neighborhoods for

2 all three metrics simultaneously. In addition, there are only nine neighborhoods in the top 10% of

3 neighborhoods for any two of the three metrics (marked in red). This suggests that resources sent

4 to these nine neighborhoods may address two of the three goals at once. However, overall it can

5 be concluded that the goals of prioritizing neighborhoods with high collision rates, speed violation

6 rates, and school zone densities for enforcement are not necessarily complementary to one another,

7 and indeed, conflict.

8 Neighborhoods within the top 10% for only one metric include 32 neighborhoods for

9 EPDO/km (identified in blue), 31 neighborhoods for SVI (identified in green), and 36

10 neighborhoods for school zone densities (identified in yellow). All three top 10% criteria groups

11 have an average calculated metric that is more than double the average for all 388 neighborhoods,

12 but they have values in the other two metric categories close to or even below the average of all

13 neighborhoods. For instance, the 2012-2014 average EPDO frequency of the neighborhoods

14 exclusively in the top 10% of collision sites is 11.9 EPDO/km, which is almost three times the

15 average EPDO frequency for all 388 neighborhoods (4.3 EPDO/km). However, the average SVI

16 of those neighborhoods exclusively in the top 10% of collision sites is 0.3 SVI, mirroring the

17 average for all neighborhoods. In addition, those neighborhoods' average school zone density is

18 only 0.4 school zones per square kilometer (sq.km), which is about half of the average for all

19 neighborhoods (0.7 school zones/sq.km). Similar observations can be made for the other two

20 groups of neighborhoods that fall exclusively in the top 10% of the speed violation metric or school

21 zone density metric. These observations imply that allocating resources to the blue, green, and

22 yellow neighborhoods shown in Fig. 2 will address high enforcement demand for only one of three

23 deployment goals. Thus, these goals are in conflict. If program managers want to address

1   conflicting program goals at the same time, they must trade off and compromise when allocating

2   resources to meet these goals, which is difficult without support from a mathematical tool.

3   The total number of enforcement shifts made in September 2014 was used to fix the total

4   number of shifts available for allocation over one month. The COE MPE program employs 20

5   operators, who are deployed in 10-hour shifts that occur twice daily, from 6 am to 4 pm, and 4 pm

6   to 2 am. A shift consists of one operator in one vehicle. In September 2014, a total of 458 shifts

7   were deployed to 231 enforcement sites located in 135 neighborhoods across the city. An operator

8   will visit anywhere from one to four sites during one shift, with an average of 6.7 hours spent on

9   the enforcement task itself per 10-hour shift. The 458 shifts made in September 2014 was used in

10   Eqn. 2 ($P = 458$).

11   Also, the actual number of shifts made in each month of 2013 and 2014, in each Edmonton

12   neighborhood i, were used to determine the minimum and maximum number of shifts available

13   for allocation in September 2014 (L_i and U_i in Eqn. 3). According to the COE MPE deployment

14   data from 2013-2014, neighborhoods were classified as receiving 1) high attention, 2) medium

15   attention, and 3) no attention. The first group consists of about 30 neighborhoods that were visited

16   each month over the two years of 2013 and 2014, and assigned a minimum of 240 shifts each

17   month (which is about half the total shifts available per month). This group of neighborhoods had

18   a minimum of 8 shifts, and maximum of 49, allocated per month. The medium attention group

19   consisted of 186 neighborhoods that were visited more occasionally, with a minimum of zero and

20   maximum of 7 shifts per month. The remaining 172 neighborhoods were not visited at all over the

21   two years. To correspond more closely to the actual needs of the Edmonton's MPE program, we

22   set the constraints L_i and U_i using the above information for the following application. However,

23   this may be changed depending on the particular requirements, needs, and governing regulations

24   of the MPE program.

1   **3.2   Model Application**

2   The MOLP model was used to distribute 458 MPE operator shifts in September 2014 over 388

3   Edmonton neighborhoods, based on each neighborhood's calculated EPDO/km, SVI, and school

4   zone density, as well as the bounds on shifts allocated to each neighborhood. The trade-offs

5   (between the three metrics considered) of different solutions will be required when they are

6   considered simultaneously. Usually there is not a single optimal solution but a set of optimal

7   solutions (known as Pareto optimal solutions); at each of these optimal solutions, one objective

8   cannot be increased without reducing at least one of the others (*22*). In this application, we used

9   the generalized differential evolution 3 algorithm (GDE3) to find the Pareto solutions set. GDE3

10   is a widely used multi-objective evolutionary algorithm (MOEA) that has been shown to

11   outperform other MOEAs (such as the non-dominated sorting genetic algorithm) in finding

12   solutions with fewer iterations (*23*, *24*). An open-source MOEA Java Framework (*25*) was used to

13   execute the GDE3 algorithm in searching for Pareto solutions (run on a Dell Precision T1700

14   workstation running Windows 7 with 3.6 GHz processor and 8 GB RAM). The parameter settings

15   used in this algorithm included a population size of 200, crossover rate of 0.1, and step size of 0.5.

16   A population size of 200 was used because we felt that this would be large enough to provide good

17   coverage of the Pareto "surface", but not so large as to completely overwhelm MPE managers who

18   would be responsible for choosing one solution among the Pareto set. The crossover rate and step

19   size values chosen (0.1 and 0.5, respectively) are both within the recommended range for the GDE3

20   algorithm (*23*). The algorithm's iterative process is stopped when the number of iterations reaches

21   a predefined limit.

22   200 solutions were obtained and they represent MPE resource allocation solutions that are

23   optimal when considering the three objective functions of Eqn. 1. All 200 solutions are plotted as

24   points in Fig. 3 using the Visual Co-Plot software (*26*). MPE program managers are expected to

1 choose a solution from this set based on their specific needs for the month, and what trade-offs

2 among the objectives are considered acceptable.

3
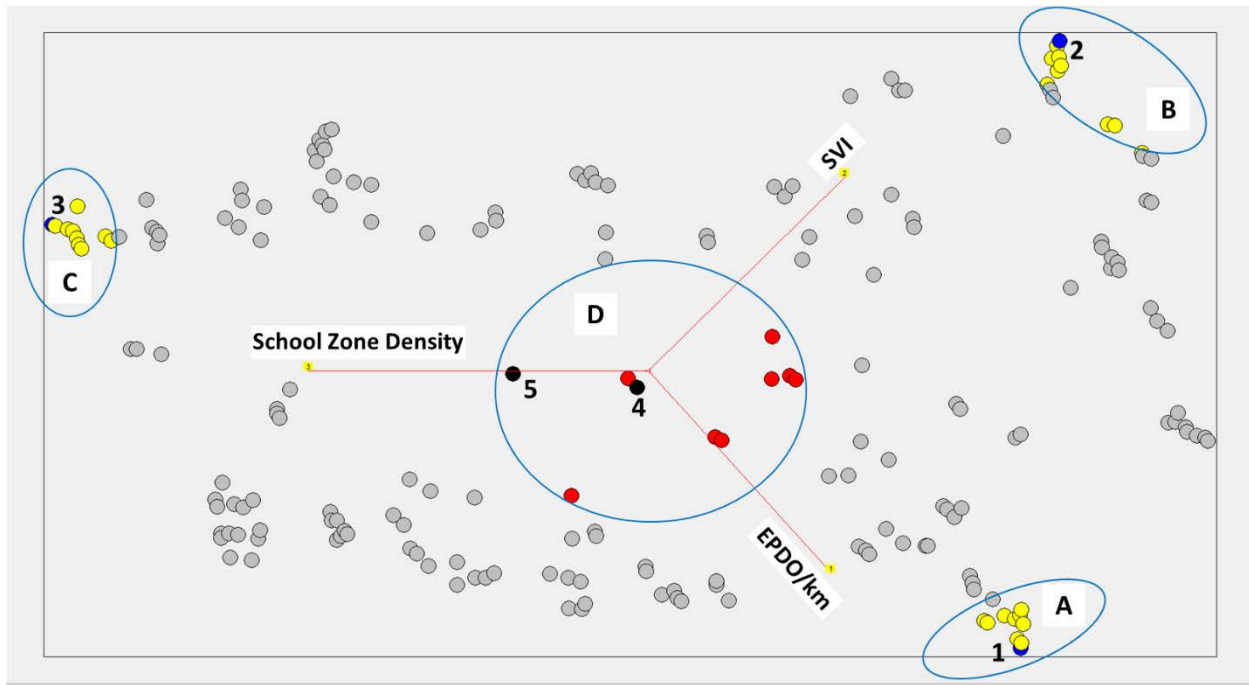
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5 **FIGURE 3 Pareto solutions from the MOLP model.**

6

7 Each axis in Fig. 3 represents a metric associated with one of the Eqn. 1 objective functions.

8 There are three circles labeled A, B, and C located beyond the ends of the axes; solutions contained

9 in these circles are identified to have metric values within the top 5% of the metric represented by

10 the axis on which they lie (10 points per group). In addition, there is one point marked in blue in

11 each circle (labeled 1 in circle A, 2 in circle B, 3 in circle C). These points are located at the

12 extreme ends of each axis and represent the highest value of the corresponding axis metric. Each

13 point represents the result obtained by maximizing one of the three objective functions of Eqn. 1.

14 Choice of each of these solutions represents the scenario where program managers have decided

15 to allocate all enforcement resources to maximizing the one corresponding metric alone, without

16 regard for the two others. The solutions in, say, Group A have high values of the EPDO/km metric

(first objective function in Eqn. 1), but exhibit a range of values of the other two metrics. Selecting a solution contained within one of these groups represents a high-level decision to give greater priority to that one deployment criteria over the others.

The points in circle D represent solutions that are the most balanced among the three objectives in Eqn. 1. Specifically, they represent the 10 points (5% of solutions) with the shortest Euclidean distance to the intercept, with the black point labeled "4" being the closest of them all. The solutions in this group were found to have relatively average values for each of the three metrics represented. Therefore, if MPE program managers are aiming to find deployment resource allocation plans that best balance all three deployment objectives, they would consider these solutions.
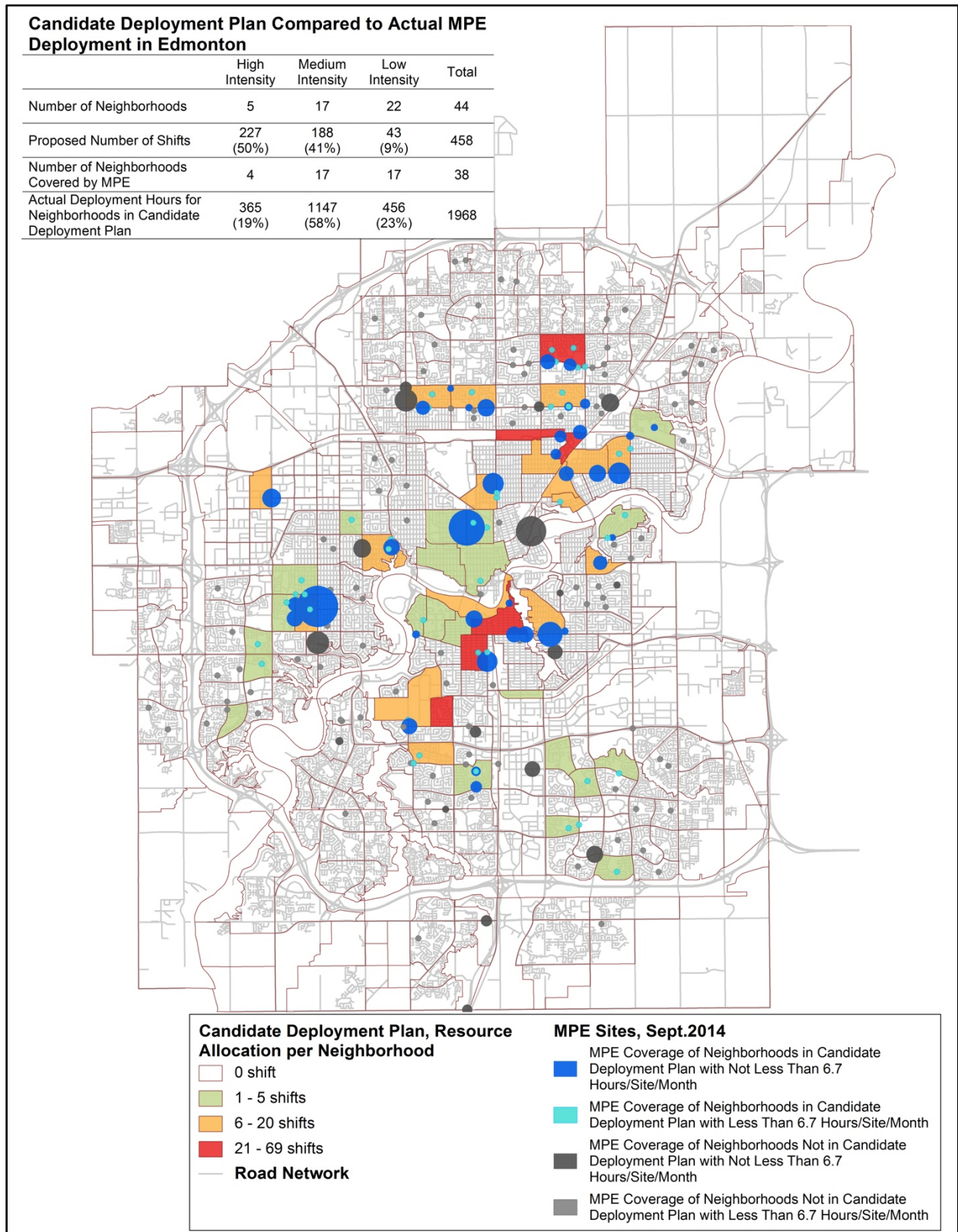
Solutions (represented by grey points) positioned between any two of the three axes exhibit relatively high values for two of the three metrics. If MPE program managers are looking to fulfill program goals that are more nuanced (i.e., somewhere between the extremes of focusing on one goal versus balancing all of them), they might focus on one of these solutions.

Overall, the model delivers deployment solutions that simultaneously consider the three deployment goals at varying relative degrees of importance. MPE program managers are provided a diverse set of solutions that yield optimal deployment allocations for any configuration of program priorities called for in a given month. In addition, the variety of options available, even when narrowed down to meet a focused program objective that is in place for longer than a single month, allows MPE program managers to change the deployment plan from month to month within that same objective. This will help to maintain the perception of unpredictability (in time and location) of enforcement activities.

3.3   Illustrative MOLP Model Solution

Here we present one candidate deployment plan for a typical September in the city of Edmonton

1 (COE). As previously mentioned, September is the beginning of the school year for kindergarten

2 through grade 12 (as well as post-secondary), and the COE MPE program will typically commit a

3 significant portion of enforcement resources to school zones at this time. Therefore, we illustrate

4 the deployment results of one potential deployment plan—solution 5, shown as a black point in

5 circle D in Fig. 3. This solution gives the highest priority to the school zone criterion among the

6 solutions in D (recall that D identified the 10 solutions that provide the most balance among the

7 three objectives in Eqn. 1). Fig. 4 shows the neighborhoods identified in the plan, which are colored

8 according to the level of proposed enforcement intensity. In addition, these results are shown

9 against the actual MPE deployment made in Edmonton in September 2014. Specifically, Fig. 4

10 uses circles to represent the MPE sites actually visited by program operators during the month.

11 These circles are differentiated by color and size. Firstly, blue represents a road segment

12 enforcement site located in at least one of the neighborhoods proposed by the plan; grey represents

13 sites actually visited in neighborhoods not included in the candidate plan. Secondly, the size of the

14 circle indicates the amount of enforcement time spent at each site over the month; the larger the

15 circle is, the more time spent at the site. During a typical 10-hour shift in September 2014,

16 operators spent an average of 6.7 hours on enforcement activities (with the balance spent in travel

17 and other non-enforcement activities). However, sites that had less than 6.7 hours of enforcement

18 over the month are represented by a lighter blue or grey colored dot that is not to scale (as they

19 otherwise would be too small to be seen on the map).

Candidate Deployment Plan Compared to Actual MPE Deployment in Edmonton

	High Intensity	Medium Intensity	Low Intensity	Total
Number of Neighborhoods	5	17	22	44
Proposed Number of Shifts	227 (50%)	188 (41%)	43 (9%)	458
Number of Neighborhoods Covered by MPE	4	17	17	38
Actual Deployment Hours for Neighborhoods in Candidate Deployment Plan	365 (19%)	1147 (58%)	456 (23%)	1968

Candidate Deployment Plan, Resource Allocation per Neighborhood

- ☐ 0 shift
- 🟩 1 - 5 shifts
- 🟧 6 - 20 shifts
- 🟥 21 - 69 shifts
- ── Road Network

MPE Sites, Sept.2014

- 🔵 MPE Coverage of Neighborhoods in Candidate Deployment Plan with Not Less Than 6.7 Hours/Site/Month
- 🔵 MPE Coverage of Neighborhoods in Candidate Deployment Plan with Less Than 6.7 Hours/Site/Month
- ⚫ MPE Coverage of Neighborhoods Not in Candidate Deployment Plan with Not Less Than 6.7 Hours/Site/Month
- ⚫ MPE Coverage of Neighborhoods Not in Candidate Deployment Plan with Less Than 6.7 Hours/Site/Month

FIGURE 3 Candidate and actual MPE deployment plans for Edmonton, September 2014.

1   As shown in Fig. 4, 44 neighborhoods were identified in the candidate deployment plan,

2   and were further split into three categories based on the number of shifts assigned to each

3   neighborhood: high, medium, and low enforcement intensity. Firstly, 5 neighborhoods (shown in

4   red) are high enforcement intensity neighborhoods, which are assigned 227 shifts with each

5   neighborhood allocated an average of 45 shifts in September. The average school zone density of

6   this neighborhood group (based on the 2012-2014 data) is 2.1 school zones/sq.km, which is three

7   times the average of all 388 neighborhoods. The high intensity neighborhoods of this group also

8   have relatively higher values in the other two metrics, showing an average of 8.8 EPDO/km and

9   0.6 SVI per neighborhood, which are each about twice the average figures for all 388

10   neighborhoods. This indicates the three program goals are all addressed with a high level of

11   enforcement, but school zones receive the most enforcement, given that the school zone density

12   metric for these neighborhoods (equal to triple the average school zone density for all

13   neighborhoods) is optimized in the model.

14   Secondly, 17 neighborhoods fall within the medium enforcement intensity group and are

15   marked in yellow in Fig. 4; these were assigned a total of 188 shifts, with each allocated an average

16   of 11 shifts in September. These neighborhoods have mean school zone density, EPDO/km, and

17   SVI values of 1.1 school zones/sq.km, 5.6 EPDO/km, and 0.5 SVI. The school zone density and

18   EPDO/km mean values are respectively 33% and 20% lower than those of the low intensity group,

19   while the SVI values are similar to those of the low intensity group. The reason that these

20   neighborhoods are assigned greater enforcement intensity than those in the low intensity group is

21   due to the values of the constraints in Eqn. 3. The minimum and maximum enforcement shifts

22   allowed to a neighborhood in the MOLP model were set using the actual numbers of shifts made

23   in 2013 and 2014 (this was discussed in 4.1). Most neighborhoods in the medium intensity group

24   are those that had received significant enforcement attention—10 to 51 shifts per neighborhood

1   per month. Therefore, the minimum shifts (L_i, Eqn. 3) for neighborhoods in this group were quite

2   high and they received significant enforcement attention, despite that they also exhibited the lowest

3   average school zone density and EPDO/km among the three intensity groups.

4   Marked in green are 22 low enforcement intensity neighborhoods. They received the lowest

5   enforcement intensity, with an average of two shifts allocated to each neighborhood during the

6   month. As mentioned previously, this neighborhood group has higher mean values of school zone

7   density and EPDO/km metrics than the medium intensity group (but lower than the high intensity

8   group), and similar mean SVI value as the medium intensity group, at 1.7 school zones/sq.km, 7.1

9   EPDO/km and 0.5 SVI.

10   The statistics of the above three neighborhood categories show that the candidate

11   deployment plan efficiently utilizes one month of shifts based on resource constraints and

12   measured neighborhood enforcement needs, as per the program goals. The measures of our three

13   objective functions are widely accepted proxies of roadway traffic safety (*27–29*); optimizing the

14   allocation of enforcement resources to neighborhoods according to these measures, as we have

15   demonstrated, is expected to result in traffic safety improvements. Specifically, we would expect

16   to see reduced collisions and near misses.

17   We also compare our illustrative candidate deployment plan with the actual COE MPE

18   deployment made in September 2014. Fig. 4 shows that 93 (40%) of 231 MPE sites enforced in

19   September 2014 are located in neighborhoods included in the candidate plan; these are represented

20   in blue. The remaining 138 MPE sites (represented as grey circles) in the actual deployment were

21   in neighborhoods not covered by the candidate deployment plan. To compare how well the three

22   goals were addressed simultaneously, we compared the values of the three objective functions in

23   Eqn. 1 for the proposed resource allocation plan and the actual program deployment. To do the

24   comparison, we used hours rather than shifts as the unit for the decision variable x_i. In the actual

1   September 2014 deployment, some operators visited enforcement sites belonging to different

2   neighborhoods during one shift; however, the candidate plan assigns an operator to visit sites only

3   within one neighborhood during a shift. Thus, we multiplied the proposed number of shifts per

4   neighborhood in the candidate plan by 6.7 hours (recall this is the average time actually spent

5   doing enforcement during a shift) and calculated the three metrics (also the objective function

6   values of Eqn. 1) when x_i is in hours rather than shifts. Then, the actual hours spent enforcing sites

7   in each neighborhood in September 2014 were used to calculate the three resulting metrics values

8   for the actual MPE deployment.

9   The results indicate that the EPDO/km, SVI and school zone density metrics obtained in

10   the candidate plan are 18%, 11% and 34% higher than those of the actual September 2014

11   deployment, respectively. The actual program spent a total of 1968 hours in September 2014 doing

12   MPE in neighborhoods also identified for enforcement in the candidate plan; this accounts for

13   about two-thirds of the total September 2014 enforcement hours (3068 hours). However, the actual

14   program spent significant time in neighborhoods that were identified as warranting medium

15   enforcement intensity in the candidate plan. Neighborhoods that were identified as part of the

16   medium intensity group in the candidate plan were covered a total of 1147 hours in the actual

17   program (which is 58% of the total MPE hours assigned in the candidate plan). In contrast, the

18   actual September 2014 program spent only 19% (365 hours) and 23% (456 hours) of the total

19   hours proposed for neighborhoods in the candidate plan on neighborhoods in the high intensity

20   and low intensity groups, respectively. Conversely, the proposed proportion of total deployment

21   time for high, medium, and low intensity neighborhoods over one month in the candidate plan is

22   50% (1521 hours), 41% (1259 hours), and 9% (288 hours), with the differences among the

23   neighborhood groups based on the metrics and model constraints. This comparison indicates that

24   the actual September 2014 deployment did not invest a greater proportion of enforcement

1 resources to neighborhoods that exhibit high levels of enforcement demand, as identified by the

2 metrics of the three program goals.

3 Another difference is that the actual deployment spent 36% of total enforcement time (3068

4 hours) on 138 MPE sites in 97 neighborhoods not identified in the candidate deployment plan.

5 These 97 neighborhoods have averages of 4.5 EPDO/km, 0.4 SVI, and 1.3 school zones/sq.km, all

6 of which are at least 17% lower than the average metrics of the 44 neighborhoods included in the

7 candidate plan (with averages of 6.7 EPDO/km, 0.5 SVI, and 1.5 school zones/sq.km). Moreover,

8 it is worth noting that 83% of these 138 MPE sites not also covered in the candidate plan

9 (represented as light grey circles) were only visited 2 hours per site over the month of September

10 2014. This suggests that most of the enforcement sites not located in neighborhoods included in

11 the candidate plan may have been visited to encourage the perception of program randomness,

12 which was not an explicit goal of the proposed model. Another 17% of these 138 MPE sites

13 (marked in dark grey circles) were visited with higher intensity, at an average of 37 hours per site

14 per month. This difference in the actual allocation may be due to the COE MPE program possibly

15 having other goals or needs to address, which we cannot comment on here.

16 Overall, this application has demonstrated how the proposed model can allocate resources

17 to balance multiple and conflicting program priorities. Visualizing the candidate plan provides

18 program managers with insight on how the deployment goals can be quantitatively mapped to the

19 deployment decisions, which may make the decision process simpler and evidence-based.

20 **4.   CONCLUSIONS AND FUTURE WORK**

21 This paper describes a resource allocation model for a mobile photo enforcement (MPE) program.

22 The model uses multi-objective optimization to optimize one month of enforcement to city

23 neighborhoods, according to a set of deployment objectives. The model found optimal allocation

24 solutions for a demonstrated 3-objective MPE deployment problem in Edmonton. The problem

1   balanced enforcement presence in September 2014 at high collision sites, high speed violation

2   sites, and school zones. Each optimal solution corresponds to a set of values for enforcement

3   coverage units at three types of sites. Choosing a solution represents a decision that gives a

4   quantitative trade-off between the three goals. A candidate solution was further visualized on a

5   GIS map. It allocates one month's shifts to 44 neighborhoods, achieving higher enforcement

6   coverage than the actual deployment in September 2014, with 11%, 34%, and 18% more coverage

7   units at high speed violation sites, school zones, and high collision sites, respectively. This suggests

8   that using our optimization model produces greater efficacy in achieving program objectives than

9   the expert defined approach.

10   The proposed model facilitates deployment decisions in three ways. First, it can guide MPE

11   program managers to make resource deployment decisions that directly reflect the program's high-

12   level priorities. This has traditionally been somewhat of a "black box"—inherently qualitative and

13   imprecisely defined. Through this work, program-level goals can be better achieved, which, in turn

14   will improve the progress toward achieving Vision Zero. Second, the MOLP model results provide

15   program managers with a set of candidate deployment options that correspond to different

16   considerations and preferences. Finally, assigning shifts at the neighborhood level provides the

17   first step towards site-level MPE shift scheduling. The model to distribute and schedule

18   neighborhood shifts to predetermined enforcement sites is currently under development.

19   The model can be applied to MPE programs in other jurisdictions, simply by tailoring the

20   high-level program goals and corresponding metrics to local program specifications, as in Fig. 1.

21   Future work may include incorporation of additional neighborhood-level metrics on top of the

22   three introduced in this paper; one such candidate metric may consider other vulnerable users.

23   Also, the proposed MOLP model does not directly address how an MPE program's perception of

1   randomness may be increased; this could be included as an objective in the MOLP, or an additional

2   post-processing step.

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