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A hybrid machine-learning and optimization method for contraflow design in post-disaster cases and traffic management scenarios

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A B S T R A C T

The growing number of man-made and natural disasters in recent years has made the disaster management a focal point of interest and research. To assist and streamline emergency evacuation, changing the directions of the roads (called contraflow, a traffic control measure) is proven to be an effective, quick and affordable scheme in the action list of the disaster management. The contraflow is computationally a challenging problem (known as NP-hard), hence developing an efficient method applicable to real-world and large-sized cases is a significant challenge in the literature. To cope with its complexities and to tailor to practical applications, a hybrid heuristic method based on a machine-learning model and bilevel optimization is developed. The idea is to try and test several contraflow scenarios providing a training dataset for a supervised learning (regression) model which is then used in an optimization framework to find a better scenario in an iterative process. This method is coded as a single computer program synchronized with GAMS (for optimization), MATLAB (for machine learning), EMME3 (for traffic simulation), MS-Access (for data storage) and MS-Excel (as an interface), and it is tested using a real dataset from Winnipeg, and Sioux-Falls as benchmarks. The algorithm managed to find globally optimal solutions for the Sioux-Falls example and improved accessibility to the dense and congested central areas of Winnipeg just by changing the direction of some roads.

1. Introduction

Climate change is widely perceived as the main culprit in the recent surge of natural disasters (Helmer & Hilhorst, 2006; Van Aalst, 2006). For a timely and effective response to a disaster, transportation plays a vital role, be it during evacuation or to deploy aid to disaster-hit areas (Perry, 2007; Zheng & Ling, 2013). Hurricane Catrina in 2005 spurred a surge of research in disaster management and evacuation covering a variety of themes such as forecasting evacuation travel demand, assigning evacuees to appropriate modes, routes, and destinations, as well as developing and evaluating various traffic management strategies to streamline the evacuation operations (He, Zheng, Peeta, & Li, 2017). Emergency evacuation planning is viewed as a network design problem, in the sense that altering some features of a transport network (such as network topology design, intersection design, and traffic management) aiming to help and facilitate the evacuation (Sheffi, Mahmassani, & Powell, 1982). One effective measure is to change road directions aiming to facilitate emergency evacuation or first-responder operations (known as contraflow), that is, to reverse the direction of a road to provide more capacity to the opposite direction. In other words, if it is a two-way road, it becomes a one-way road, or if it is a one-way road, the direction is reversed. Hence, contraflow is synonymous with the one-way network design problem or arc reversal problem. Moreover, the contraflow strategy stands for temporarily utilizing the available transport infrastructure without relying on major capital-intensive and time-consuming infrastructure investments such as road construction projects. In addition to emergency situations, the idea of contraflow has also been recognized as a traffic control measure by practitioners and scholars, especially when it is synthesized with other control measures (i.e. parking restriction, ramp metering, toll roads) to enhance traffic circulation in urban areas (Bagloee & Sarvi, 2015, 2017; Bagloee, Asadi, & Richardson, 2012; Bagloee, Sarvi, & Wallace, 2016; Du & Pardalos, 1993). In fact, a highway design book (AASHTO, 2011), clearly favors one-way roads

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over two-way roads on the basis of fewer traffic conflicts at junctions which results in higher speed and lane capacity. According to Zhang and Gao (2007), the one-way scheme is a widely used policy in China to alleviate traffic congestion during the peak hour time.

Despite the merits of the contraflow, a reliable and practical methodology tailored to real-life cases is a rare currency, that is due to inherent theoretical and computational complexities of the problem (Murray-Tuite & Wolshon, 2013). To this end, this study attempts to address the following task: given a large-sized road network, and a travel demand scenario (which could be an evacuation scenario: how many people are supposed to be evacuated from where to seek shelter where), change the direction of the roads such that the total traverse time is minimized. By calling it the contraflow problem (CP), first, the CP is formulated as a bilevel programming problem to minimize the total traverse time at the upper level, while accounting for route-choice behavior (as a sub-problem) at the lower level. Second, to cope with the complexity of the CP, a hybrid Machine-Learning and Optimization approach (known as ML-O) recently developed and validated in (Bagloee, Asadi, Sarvi, & Patriksson, 2018b) is employed as a solution method. The ML-O essentially incorporates a surrogate model in which a nonlinear objective function is replaced with a linear function while some of the constraints and variables are also dropped resulting in a computationally efficient method. The proposed methodology is tested using a road network of medium size from Sioux-Falls and a large-sized network of Winnipeg.

The kernel of the ML-O is to strip the original problem from its difficult components (i.e. nonlinear functions and constraints) and instead to spread it out over a binary space with a high degree of freedom. For example, in the Winnipeg case-study, the total number of original decision variable is 83, whereas, when it is formulated in a binary space, it increases three folds (i.e. 249 binary variables). Hence, instead of solving a nonlinear, discrete bilevel problem with 83 integer variables, the ML-O solves a linear binary single-level problem which is much easier to handle.

The algorithm manages to find globally optimal solutions for Sioux-Falls and improves accessibility to the dense and congested central areas of Winnipeg just by changing the direction of some roads. The main contribution of the proposed methodology can be summarized as follows. (i) the contraflow problem (CP) is formulated as a bilevel, nonlinear and discrete problem subject to solving a traffic assignment problem. (ii) the general ML-O algorithm has been customized to solve the CP. To this end, the triplet structure of discrete solution (i.e. 0,1, 2) replaces the binary structure (i.e. 0, 1) in the original ML-O algorithm. Therefore, the ML-O is now able to solve much generalized bilevel problems which need greater details of decision variables.

The outline of the paper is as follows, Section 2 provides a review of the relevant studies in one-way design as well as emergency evacuation. In Section 3, the mathematical setup of the methodology is articulated. In Section 4, the proposed ML-O solution algorithm is discussed. Numerical evaluations are provided in Section 5 and the paper is concluded in Section 6.

2. Literature review

Though bilevel programming seems to be a natural way to formulate the network design problems including the CP, it comes at the cost of significant computational complexity. The CP can be considered as a two-player game consisting of a traffic authority and drivers. With an intention of improving traffic circulation, the former makes changes to the transport network (e.g. changing the roads' direction) based on which the latter will change their driving habit (e.g. changing their usual routes). Drivers; driving change can be accounted for by solving the traffic assignment problem. Such a setup can be formulated as a bilevel problem also known as Stackelberg game (Stackelberg, 1952). Generally speaking, a bilevel problem even at the easiest possible instance (all functions are linear and all variables are continuous) is NP-hard (Jeroslow, 1985), that is, as the size of the problem (number of constraints and variables) increases, the problem becomes computationally burdensome. Therefore, some studies have instead formulated the CP as a single-level optimization problem which are reviewed first. A review of the bilevel approaches is provided in the next section.

2.1. Single-level optimization

Tuydes and Ziliaskopoulos (2004) identify optimal contraflow operations using a system optimal dynamic traffic assignment (DTA) method based on the cell transmission model (CTM). Application of the CTM to large-sized networks is computationally prohibitive as it requires dividing the road links into small cells which adds to the size of the network. Kalafatas and Peeta (2009) solve the CP based on a graph-theoretic transformation of the CTM aiming to enhance the computational efficiency. Tuydes and Ziliaskopoulos (2006) employ a tabu search method (a metaheuristic approach) to find an optimal reversibility design that reduces total system travel time in which traffic circulation is based on the CTM. Kim, Shekhar, and Min (2008) formulate the CP as a mixed integer linear program (MILP) based on "bottleneck relief", which identifies the bottlenecks and increase their capacities by contraflow. Zhang and Zhong (2013) extend the idea of contraflow to the optimal allocation of the lanes to opposite directions. The problem is formulated as a binary complementarity problem which is then transformed to a relaxed knapsack problem to be solved with a commercial optimization software. Foulds, Duarte, do Nascimento, Longo, and Hall (2014) address a similar problem, namely optimal restriction (prohibition) of certain turns at intersections for which a successive linear approximation is used. He et al. (2017) formulate shelter assignment and contraflow operations as a mixed integer linear program and develop a Benders decomposition algorithm to solve for a medium-sized traffic network of the Dallas-Fort Worth area. Rebennack, Arulselvan, Elefteriadou, and Pardalos (2010) provide a comprehensive study of the network flow problems with arc reversal capabilities. They conclude that the single-level evacuation problem with arc reversal capability and the problem of the total cost minimization resulting from arc switching costs are inherently NP-hard.

2.1. Bilevel optimization

A variety of metaheuristic methods has been proposed for the CP formulated as a bilevel problem, such as simulated annealing (Lee & Yang, 1994) and genetic algorithm (Zargari & Taromi, 2006). El-Sbayti (2008) formulates the contraflow design problem while accounting for the traffic circulation as a DTA in the lower level problem for which an iterative heuristic solution method is developed. Meng and Khoo (2008) propose a genetic algorithm integrated into a traffic simulator to find optimal direction for 18 roads of a medium-sized traffic network. Xie, Lin, and Waller (2010) discuss a dynamic evacuation network optimization problem that incorporates lane reversal and crossing elimination strategies to complement one another by increasing capacity in specific directions during the evacuation. In their study, the lower level is a dynamic traffic assignment formulation based on the CTM. As a solution algorithm, an integrated Lagrangian relaxation and tabu search method is devised to approximate optimal solutions through an iterative evaluation process. Similarly, Xie and Turnquist (2011) address the contraflow problem while attempting to eliminate crossing movements at junctions, for which a heuristic approach based on Lagrangian relaxation and tabu search is developed and applied to a medium-sized network. Karoonsoontawong and Lin (2011) extend the CP to time-varying lane reversal design problem using a CTM for which they apply a genetic algorithm to a medium-sized network to decide on the direction of 14 roads. Afandizadeh et al. (2013) employ a simulated annealing algorithm, considering the traffic assignment model (in the lower level) as a stochastic user equilibrium. Hua, Ren, Cheng, and Ran (2014) develop a branch-and-bound algorithm mixed with a genetic algorithm to solve the contraflow problem while giving priority to public transport modes.

In evacuation related applications, a proper and speedy damage assessment of the road infrastructure is of highest importance (Özdamar & Ertem, 2015). With today's technology, satellite images and remote sensing can assist authorities in their operational planning and decision making (Sakuraba et al., 2016). In particular, Artificial Intelligent (AI) plays a pivotal role to process satellite images as well as information derived from social networks and media aiming to provide accurate and real-time damage estimation (Holguín-Veras, Jaller, & Wachtendorf, 2012; Koyama, Gokon, Jimbo, Koshimura, & Sato, 2016; Reddy, Reddy, & Reddy, 2017). Spatial planning provides tools to government authorities that support integrated response strategies as part of the disaster management (Nakanishi, Matsuo, & Black, 2013). To this end, Bono and Gutiérrez (2011) develop a method to define the urban accessibility landscape in the aftermath of earthquake damage, by combining simple graph theory concepts and GIS-based spatial analysis to assess how the urban space accessibility decreases when the road network is damaged. Moreover, in the wake of the devastating 7.0 earthquake in Haiti, social media (twitter, facebook etc.) have become, for the first time, a major hub of information which was greatly exploited by NGOs (non-profit organizations) to organize and plan their relief operations (Muralidharan, Rasmussen, Patterson, & Shin, 2011). The AI can tap into such precious source of data (Kim & Hastak, 2018; Middleton, Middleton, & Modafferi, 2014; Steiger, Albuquerque, & Zipf, 2015) and draw up a real-time picture of the disaster-hit areas. Hence, in the aftermath of a disaster, it is possible to quickly assess damages to the road infrastructure. This information is then passed on to disaster management authorities for a variety of operations including evacuation plans.

The findings of the literature review can be summarized as follows:

- The CP, even formulated a single-level optimization problem, is essentially NP-hard.
- Some scholars resort to exact or approximation methods which are hard to scale them to real-life cases.
- A clear majority of the past research used CTM mainly to capture traffic dynamics better than the static model which limits their applications to real-life and large-sized examples (due to high computational costs).
- As can be seen, the capability of addressing large-sized examples in the past research is a rare currency.

To this end, the CP in this paper is formulated as a bilevel problem for which a solution method applicable to large-sized traffic networks is developed. Although the CP is an NP-hard problem, it does not preclude us from formulating it as a bilevel problem, nor does it interdict searching for a heuristic problem tailored to large-scale case-studies. Evidently, what has been proposed in this research is an aggregate model which sacrifices the detail-level analysis of the CTM and DTA for the sake of practical applications. As a result, the proposed model can be applied at a network level considering an entire city which will then come handy to address other related network-wide problems such as identifying locations of the aid centers. In other words, the proposed methodology will set a foundation for strategic and macro-level-type problems related to the disaster management as well as traffic control schemes for which CTM and DTA models come short.

Often, as discussed in the literature review, to solve problems like the contraflow for large-sized examples, metaheuristic methods such as genetic algorithm (GA) are used. Instead of the GA, the ML-O is used which has numerically been proven to be superior as discussed in (Bagloee et al., 2018b). However, given the nature of the CP as a bilevel problem (and hence to be NP-hard), resorting to heuristic methods when solving for large-sized examples is inevitable and the ML-O is one of them.

3. Mathematical formulation of the CP

To formulate the CP, consider a set of two-way roads as candidates to become one-way. In the optimal contraflow scenario, a two-way candidate road, connecting two nodes (denoted by i and j) may face three possible options:

(i) to remain intact as it is, denoted by the binary decision variable $y_{ij}^1 = 1$ (equal to 0 otherwise),
(ii) to turn to a one-way road from i to j, hence the arc $j \to i$ is disconnected and its capacity is added to the capacity of the arc $i \to j$, denoted by the binary decision variable $y_{ij}^2 = 1$ (equal to 0 otherwise),
(iii) to turn to a one-way road from j to i, hence the arc $i \to j$ is disconnected and its capacity is added to the capacity of the arc $j \to i$, denoted by the binary decision variable $y_{ij}^3 = 1$ (equal to 0 otherwise).

Obviously, the above options can also be applied to a one-way road (one can consider a one-way road as a two-way road in which the capacity of the other direction is zero).

Each candidate road is associated with a cost accounting for marking, signage, signal, and other external expenses. There exists a budget based on which the aim is to select a subset of the candidate roads and to assign proper directions such that the total traverse time is minimized. Obviously, any changes to the setup of the road network (including the direction of the road) are conducive to the drivers changing their usual routes which itself is an optimization problem (Beckmann, McGuire, & Winsten, 1956), known as the traffic assignment problem (TAP).

A definition of all the notations is first provided followed by elaborating on a formulation for the CP.

Notation

A, A' sets of existing roads and candidate two-way roads, respectively,

B budget to cover the expenses such as signage, marking signals etc. to turn a two-way road to a one-way road

$y_{ij}^1, y_{ij}^2, y_{ij}^3$ the trio binary decision variables of the directions of a two-way road $(i, j) \in A'$; $y_{ij}^1 = 1$: no change to the road's direction, $y_{ij}^2 = 1$: make it one-way from i to j, $y_{ij}^3 = 1$: make it one-way from*j*to*i*. Note that, there always exists: $y_{ij}^1 + y_{ij}^2 + y_{ij}^3 = 1$.

c_{ij} the implementation costs (such as marking, signage etc.) pertaining to turn a candidate two-way road $(i, j) \in A'$ a one-way road

x_{ij} a continuous variable denoting traffic flow on the road $(i, j) \in A \cup A'$,

$t_{ij}(x_{ij})$ travel cost (or time or delay) of the road$(i, j) \in A \cup A'$, defined by a differentiable strictly increasing function of road's traffic flow x_{ij} (also referred to as a delay function). The widely-used BPR function (Bureau of Public Road (BPR, 1964)) is adopted in this study which is $t_{ij}(x_{ij}) = t_{ij}^0(1 + .15(x_{ij}/\nu_{ij})^4)$, where t_{ij}^0 is free-flow travel time (minutes) and ν_{ij} the capacity (vehicles per hour) of the respective road,

W	set of origin-destination pairs,
q_w	travel demand pertinent to origin-destination $w \in W$,
P_w	set of paths between origin-destination $w \in W$,
h_p	total flow on the path $p \in P_w$,
$\delta_{ij,p}$	link-path incident index, 1 if link $(i, j) \in A \cup A'$ belongs to path p and 0 otherwise,
M	a sufficiently large value,
Z	total travel time (the objective function),
CP	contraflow problem,
TAP	traffic assignment problem,
DTA	dynamic traffic assignment,
CTM	cell transmission model,
MILP	mixed integer linear program,
UE	user equilibrium,
ML-O	machine-learning and optimization,
ILP	integer linear programming,

The bilevel CP can be written as follows:

$$\text{CP} : \underset{x_{ij}, y^1_{ij}, y^2_{ij}, y^3_{ij}}{Minimize}\ Z(x_{ij}, y_{ij}) = \sum_{(i,j)\in A\cup A'} x_{ij}.\, t_{ij}(x_{ij}), \tag{1}$$

subject to

$$\sum_{(i,j)\in A'} c_{ij}.(y^2_{ij} + y^3_{ij}) \le B, \tag{2}$$

$$\begin{cases} y^1_{ij} + y^2_{ij} + y^3_{ij} = 1 \\ y^l_{ij} = \{0, 1\} \quad (i, j) \in A', l \in \{1, 2, 3\} \end{cases} \tag{3}$$

$$\underset{x_{ij}}{Minimize} \sum_{(i,j)\in A\cup A'} \int_0^{x_{ij}} t_{ij}(x)\, dx \tag{4}$$

subject to

$$\sum_{p\in P_w} h_p = q_w, \quad w \in W, \tag{5}$$

$$x_{ij} = \sum_{w\in W} \sum_{p\in P_w} h_p \delta_{ij,p}, \quad (i, j) \in A \cup A', \tag{6}$$

$$x_{ij} \ge 0, \quad (i, j) \in A \cup A'. \tag{7}$$

$$\begin{cases} x_{ij} \le M.(y^1_{ij} + y^2_{ij}) \\ x_{ji} \le M.(y^1_{ij} + y^3_{ij}) \end{cases} \quad (i, j) \in A', \tag{8}$$

Eq. (1) is to minimize the total travel time in the upper level Given a road denoted by start node i and end-node j, the number of people driving through (x_{ij}) multiplied by their respective travel time (t_{ij}) is the total travel time spent on the road (i, j). By summing them up over all the roads, the total travel time is calculated. The notations beneath the "minimize" sign indicate all the variables of the CP to be assigned values when the CP is solved. Constraints (2) and (3) ensures the feasibility of the trio binary solution $(y^1_{ij}, y^2_{ij}, y^3_{ij})$ with respect to the costs and the budget. Note that in Constraint (2) the cost of turning a two-way road (i, j) to a one-way road $i \to j$ is assumed identical to that of the cost of $j \to i$ irrespective of the ultimate direction. However, this constraint can be easily rewritten to include different costs for different directions. Furthermore, the sum of the term in the parentheses is either 1 or 0 ($y^2_{ij} + y^3_{ij} = \{0, 1\}$). In the lower level (4)–(8), the traffic assignment problem (TAP) is formulated based on the Beckmann's user equilibrium (UE) traffic flow. Eq. (4) also known as the Beckmann function was introduced in 1956 which was a breakthrough, in the sense that an equilibrium traffic flow is formulated as a tractable convex optimization problem with seemingly unorthodox shape (i.e. sigma and integral operands) Beckmann et al., 1956). The main idea behind the UE traffic flow is that drivers always choose the shortest paths. Constraint (8) ensures that the traffic flow of a particular direction complies with the respective decision, that is to comply with the three options discussed above (note $M$is a sufficiently large value below):

- $y^1_{ij} = 1$ and $y^2_{ij} = 0, y^3_{ij} = 0$ the respective road remains intact, both directions are open $x_{ij} \le M = M(1+0)$ and $x_{ji} \le M = M(1+0)$
- $y^2_{ij} = 1$ and $y^1_{ij} = 0, y^3_{ij} = 0$: direction $i \to j$ is decided to be open while the opposite direction is closed $x_{ij} \le M = M(0+1)$ and $x_{ji} \le 0 = M(0+0)$
- $y^3_{ij} = 1$ and $y^1_{ij} = 0, y^2_{ij} = 0$: direction $j \to i$ is decided to be open while the opposite direction is closed $x_{ij} \le 0 = M(0+0)$ and $x_{ji} \le M = M(0+1)$

Remark 3.1. It is important to have some insight about a commensurate value of M, for which, constraints (8) provide a valuable clue that is the total travel demand can be considered as an upper level bound of M. In fact, M is the maximum possible traffic volume that a road can process.

Remark 3.2. The above formulation can be interpreted as a leader-follower Stackelberg game (Stackelberg, 1952; Yang, Zhang, & Meng, 2007). The leader (in this case disaster manager or traffic authority) first decides on the values of the triples variables $(y^1_{ij}, y^2_{ij}, y^3_{ij})$, that is, what two-way roads must be rewired to one-way and in what direction? The followers (in this case evacuees or drivers) take the new changes in the directions of the roads into account and change their routes to find the shortest paths (i.e., to find the UE traffic flow), which results in new values of the traffic flows x_{ij} derived from solving the TAP. It is postulated that evacuees will have a good spatial knowledge of the road closure conditions on real time basis which is not a far-fetched proposition with today's technologies such as variable message signs, radio traveler information, live google traffic map, Waze, smart and advanced GPS, as well connected vehicle technologies (i.e. On-Board Unit and Road-Side Unit) (Bagloee, Ceder, & Bozic, 2014; Bagloee, Kermanshah, & Bozic, 2013; Bahaaldin, Fries, Bhavsar, & Das, 2017; Edelstein, 2018; Moon, 2017; Tran, 2018). Therefore, given a feasible solution for $(y^1_{ij}, y^2_{ij}, y^3_{ij})$, the CP becomes simply a TAP which is a convex problem and can be efficiently solved using off-the-shelf commercial software. Therefore, the crux of the problem is to find a feasible solution for the triples $(y^1_{ij}, y^2_{ij}, y^3_{ij})$ for which the authors resort to a machine-learning technique, discussed in the next section.

Remark 3.3. The contraflow problem is modeled in a very simple way: should do nothing (y^1_{ij}) or should convert to opposite direction (y^2_{ij}, y^3_{ij}). One may ask to split the decision at lane level in the sense that to change the direction of the lanes. For example, for a three-lane road from i to j one may convert one lane into j to i and use the remaining two for i to j. To this end, it is worth noting that, for the sake of operation and practical implications, it is easier, less expensive and more doable for traffic authorities to close or reverse direction of a road rather than a lane of a road. Moreover, contraflow schemes are regarded as temporary policies to manage traffic flow for which speedy implementation is of highest importance. Therefore, a detailed lane-based contraflow scheme is associated with special lane-marking, signage as well as serious traffic safety concerns. Nevertheless, the proposed methodology can be easily generalized to consider the lane-based contraflow cases just by associating each lane with additional binary variables which result in more variables and constraints followed by higher computation time.

4. ML-O solution algorithm

In this section, a hybrid method composed of a supervised learning technique and an integer program tailored to real-life applications is developed. To put the supervised learning technique in perspective, consider that one wants to predict the height of people from their age, gender, and race. Hence, he does a survey to collect heights as well as age, gender, and race of a number of people. He then trains a machine learning model in which the inputs are age, gender and race and the output is height. This is called a supervised learning in the sense that the outcome was already known in the dataset. In contrast, for the unsupervised learning, the outcome is not known for which one good example is to predict engine failure by just recording noisy trends in heat, pressure and sound data of the engine.

The fact that the CP is a bilevel problem is enough to make it NP-hard (Ben-Ayed & Blair, 1990). Its computational complexity can be addressed by decomposing it into two sub-problems corresponding to two upper and lower bound values of the objective function. Such schemes usually become time-consuming for large-sized networks. As an alternative, the authors have developed a hybrid method for general bilevel problems consisting of a supervised learning technique and an integer programming problem (Bagloee et al., 2018b). This method denoted by ML-O is also employed here as a solution algorithm.

The ML-O algorithm initiates with a feasible binary solution $(y^1_{ij}, y^2_{ij}, y^3_{ij})$ for which, the TAP is solved to calculate the value of the objective function (1). Sometimes, the do-nothing scenario (the existing situation) can be used as a feasible solution to launch the algorithm. In other words, given a feasible solution $(y^1_{ij}, y^2_{ij}, y^3_{ij})$, the CP is solved and the value of the objective function $Z$is computed. These data (Z and $y^1_{ij}, y^2_{ij}, y^3_{ij}$) are then used to train a multivariate linear regression model as a function of the decision variables:

$$\bar{Z} = \sum\nolimits_{(i,j)\in A'} b^1_{ij}.y^1_{ij} + \sum\nolimits_{(i,j)\in A'} b^2_{ij}.y^2_{ij} + \sum\nolimits_{(i,j)\in A'} b^3_{ij}.y^3_{ij} \tag{9}$$

where $\bar{Z}$ is a linear approximation or a surrogate function of the original objective function Z and $b^1_{ij}, b^2_{ij}, b^3_{ij},$ are parameters to be calibrated. In other words, given a set of training data (Z and $y^1_{ij}, y^2_{ij}, y^3_{ij}$) an estimate of the parameters $(b^1_{ij}, b^2_{ij}, b^3_{ij},)$ is sought. The calibration process is equivalent to solve for a quadratic minimization of the gap between Z and $\bar{Z}$ subject to several linear constraints. The gap function is in fact an error function defined as $(\bar{Z} - Z)^2$ to be minimized. Considering that $\bar{Z}$ is a function of parameters $b^1_{ij}, b^2_{ij}, b^3_{ij}$. When the error index is minimized, the parameters are given appropriate values. This minimization problem is a convex problem and hence easy to solve (Greene, 2003).

One may ask why linear approximation has been used in this study. The main reason is the computational burden in the sense that the ensuing problem (as discussed below) will be an all-out linear problem which is much easier to solve. Moreover, we have numerically shown that the linear approximation is enough and adequate for the contraflow problems. However, in some other bilevel problems, depending on their level of complexities, such as water engineering (Bagloee, Asadi, & Patriksson, 2018a), a higher order of linearization might be needed.

The next step is to arrive at a new feasible and possibly a better binary solution for which the authors construct an integer linear programming (ILP) problem as follows. The ML-O postulate that the regression model, which is a linear function of decision variables, is an approximation of the original objective subject to all the binary constraints of the original problem as follows:

$$\mathrm{CP-ILP}: \bar{Z} = \sum\nolimits_{(i,j)\in A'} b^1_{ij}.y^1_{ij} + \sum\nolimits_{(i,j)\in A'} b^2_{ij}.y^2_{ij} + \sum\nolimits_{(i,j)\in A'} b^3_{ij}.y^3_{ij} \tag{repeated-9}$$

subject to

$$\begin{cases} \sum\limits_{\substack{l=\{1,2,3\}\\(i,j)\in Y1^k}} y^l_{ij} - \sum\limits_{\substack{l=\{1,2,3\}\\(i,j)\in Y0^k}} y_a \leq \ |Y1^k| - 1 \\ where: \\ Y1^k = \{(i,j)|y^{l,k}_{ij} = 1\}; \quad l = \{1,2,3\},\ (i,j) \in A',\ k = 1..\alpha \\ Y0^k = \{(i,j)|y^{l,k}_{ij} = 0\} \end{cases} \tag{10}$$

(2) and (3)

The mandate of the above CP-ILP is to render a new feasible solution $y^{l,\alpha+1}_{ij}$, $l = \{1,2,3\}$ to be used for the next iteration $\alpha + 1$. To this end, Constraint (10) plays a vital role to guarantee to find a new binary solution at the end of each iteration (Balas & Jeroslow, 1972). In Constraint (10), $Y1^k$, $Y0^k$ denote the binary variables that have taken values of 1 and 0, respectively, in past iterations until the latest iteration.

It is worth noting that (9) embeds x_{ij}, the drivers' route choices. In other words, when comparing the CP-ILP with the CP, the traffic flows have been dropped which has resulted in much fewer variables and constraints that in turn improves the computational efficiencies. Just to give a glimpse of the size of the ensuing problem consider the Winnipeg case-study, when all the link's traffic flow variables (x_{ij}) are dropped, it results in 3383 fewer variables as well as 154×154+3383 fewer constraints (see Constraints (5) and (6) and the number of links and zones which are 3383 and 154, respectively). Furthermore, notice that variables of the CP-ILP are all binary and the constraints, as well as the objective function, are all linear. This also expedites the problem's runtime and make the problem in turn pliable to commercial optimization software to be efficiently solved as an ILP problem.

To have some insight of the extent of computational efficiency of the ML-O, we refer to (Bagloee et al., 2018b) in which the numerical results of a comparison analysis with an exact method (i.e. Branch and Bound hybridized with the Benders Decomposition (Bagloee, Sarvi, & Patriksson, 2017)), have shown that the ML-O is 2.48 times faster

To have some insight of the extent of computational efficiency of the ML-O, numerical results of a comparison analysis with an exact method (i.e. Branch and Bound hybridized with the Benders Decomposition, (Bagloee et al., 2017)) have shown that the ML-O is 2.48 times faster (see Table 3 in (Bagloee et al., 2018b)).

For the next step, the new binary solution $(y^{l,\alpha+1}_{ij}, l = \{1,2,3\})$ is placed into the original CP (to simply transform it to a TAP) to calculate the total travel time $(Z^{\alpha+1})$ which provides a new training record of $(Z^{\alpha+1}, y^{l,\alpha+1}_{ij}, l = \{1,2,3\})$. The algorithm then proceeds to carry out a new regression followed by the CP-ILP and to repeat these steps. This process carries on until a pre-specified maximum number of iterations is exhausted, hence, the binary solution with the minimum value of the objective function is reported as the best solution found.

Maximum number of iteration is usually a dilemma with (meta)heuristic methods. For the ML-O, however, by tracking down the calibration of the regression model, one can have some valuable clue of when to terminate the algorithm. Numerical results of the ML-O applied to several different use-cases (i.e. project management and water engineering (Bagloee et al., 2018a; Bagloee, Sarvi, Patriksson, & Asadi, 2018c)) suggest that as a rule of thumb, 10 times the number of binary variable is a commensurate maximum number of iteration.

The proposed algorithm can be summarized as follows:

Step 0, initialization: set iteration counter $\alpha = 0$, $\alpha_{\max}$ as a maximum number of iterations, and $y^{l,0}_{ij} = 0$, $(i,j) \in A'$, $l = \{1,2,3\}$ as an initial feasible solution.

Step 1, traffic assignment: given the current feasible solution $y_{ij}^{l,\alpha} = 0,\ (i,j) \in A',\ l = \{1,2,3\}$, solve the TAP and return the value of the objective function Z^{α}.

Step 2, regression: given $y_{ij}^{l,k} = 0,\ (i,j) \in A',\ l = \{1,2,3\}$ s as well as their corresponding Z^k s being compiled till now (i.e.,$k = 1..\alpha$), calibrate a new regression function $\bar{Z}^{\alpha}$ of Eq. (9).

Step 3, update and run the integer problem: based on the current binary solutions $y_{ij}^{l,\alpha} = 0,\ (i,j) \in A',\ l = \{1,2,3\}$ and newly calibrated function $\bar{Z}^{\alpha}$, update the objective function (9) and Constraint (10) in the CP-ILP and solve the updated CP-ILP problem to find a new feasible solution $y_{ij}^{l,\alpha+1} = 0,\ (i,j) \in A',\ l = \{1,2,3\}$.

Step 4, check out termination criterion: if $\alpha < \alpha_{\max}$ then, set $\alpha = \alpha + 1$ and go to Step 1, otherwise, stop and report the best solution found (i.e., $y_{ij}^{l,*}$, Z^* where $Z^* = \arg\min_{k=1..\alpha_{\max}} Z^k$) □

4.1. Maximum number of iteration (α_{max}) as a termination criterion

Two observations of the algorithm's behavior can be regarded as intuitive clues to arrive at a commensurate $\alpha_{\max}$. (i) According to the results reported by (Bagloee et al., 2018b), early iterations are dedicated to consolidating the training of the regression function which is equivalent to the number of binary variables involved. Hence it is suggested to set the $\alpha_{\max}$ greater than ten times of the number of binary variables. (ii) One can observe the changes in the calibration parameters being updated over successive iterations, and stop the algorithm when these changes stabilize and dampen to zero after a number of iterations.

As noted above, the training involves updating the regression's parameters which happens at every iteration. Hence this is a progressive training procedure which carries on all the way till the very last iteration. It is also worth highlighting the number of regression's parameter which is identical to the number of binary (decision) variables. Given the fact that, every iteration adds only an additional record to the training dataset, in early iterations (when there are not enough records for training), one, in terms of the values of the objective function, can expect chaotic outcomes. With the same token, as the number of iterations increases, and more training records are piled up, the outcomes visibly converge.

5. Numerical tests

In this section, the numerical results of the proposed methodology applied to two case studies: Sioux-Falls and Winnipeg are discussed. The Sioux-Falls case study is a medium-sized network designed as a challenging benchmark for which the authors have already identified the optimal solutions via an exhaustive enumeration. Hence, one can investigate the capability of the proposed methodology to find an optimal solution. The Winnipeg case study is a large-sized network to challenge the methodology in a realistic application. Both datasets are made available to the research community via GitHub to be used as benchmark cases in future studies (Bagloee, 2018).

To arrive at a precise numerical result when solving a TAP, as suggested by (Boyce, Ralevic-Dekic, & Bar-Gera, 2004), the authors set "relative gap" of the size of 0.0001 as a termination criterion (it is a very fine convergence rate between successive iterations). Aa desktop computer with 64.0 GB RAM and CPU processor of Intel Xeon 3.70 GHz is employed. The algorithm is coded with Visual Basic linked to MS-Excel as an interface as well as MS-Access a database. The computer program is interfaced to EMME 3 an efficient commercial software to solve TAPs. The code also calls on GAMS (Baron solver (Tawarmalani & Sahinidis, 2005)) to solve the CP-ILP and MATLAB (MathWorks, 2016) for solving the multivariate regression.

5.1. Sioux-Falls

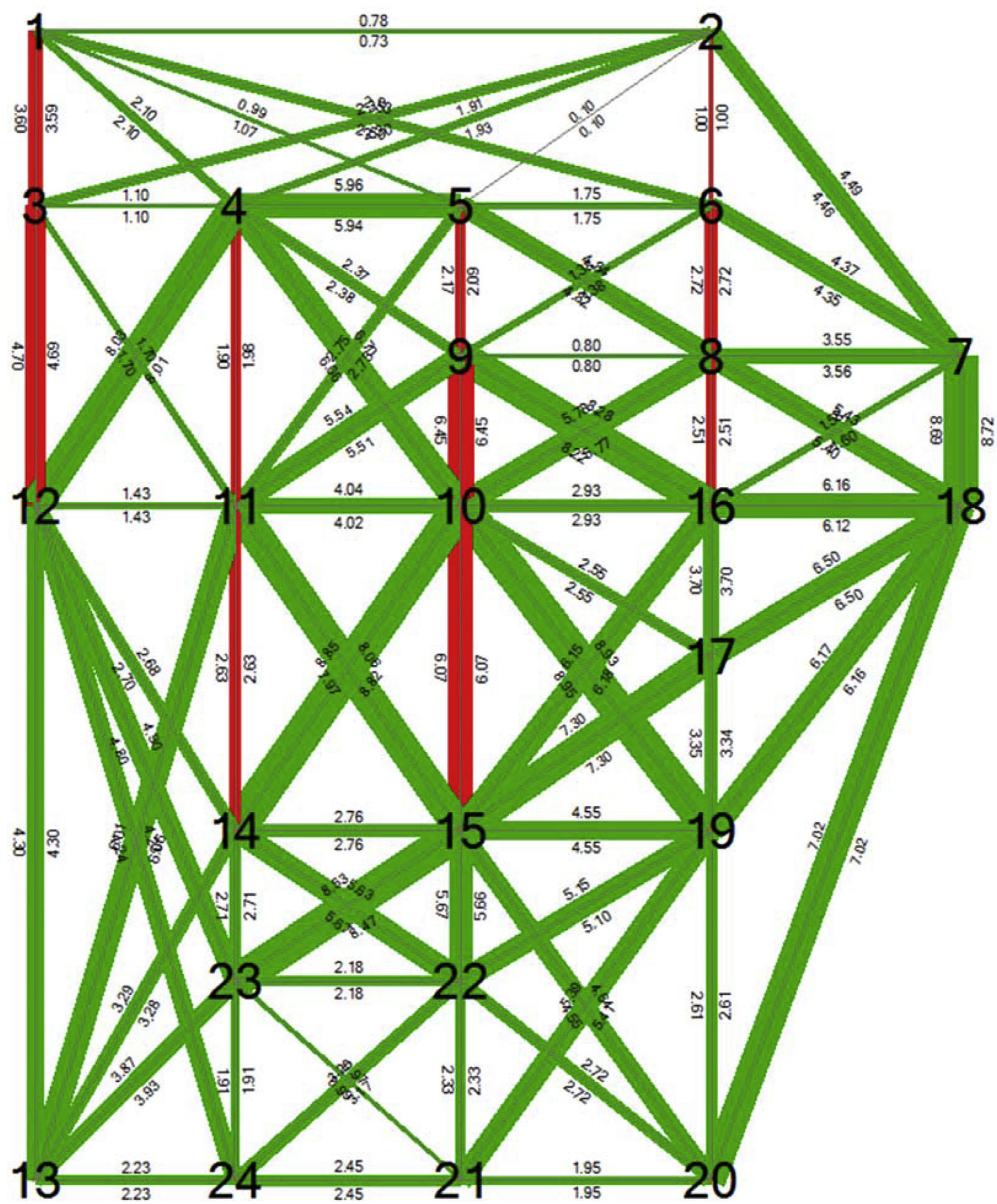
The Sioux-Falls network consists of 24 nodes and 204 directional links as shown in Fig. 1. Fig. 1 shows the traffic flow corresponding to the do-nothing scenario (when all roads are two-way) in which the total travel time (value of the objective function) was found to be 3921.741. We consider 10 two-way roads as candidates (shown red-colored in Fig. 1) which results in 3^{10} scenarios to be first enumerated by solving 3^{10} TAPs. All these possible combinations of feasible binary solutions take 30 hours, approximately. We chose 10 just for computational convenience (to be able to enumerate all the possible scenarios within an affordable time span). An additional two-way road (i.e. 11 two-way roads) would results in 90 hours enumeration computation.

It is assumed that the cost of turning each two-way road to one-way is 1 unit of cost which amounts to 10 unit of cost for all the candidates. However, to challenge the methodology the authors set the budget to 0, 1, 2, …, 10 units each, and compare the results with the enumeration as shown in Table 1.

With respect to Table 1, it seems the values of the objective function (i.e. total travel time) over various budget levels are approximately the same. To this end, it is worth highlighting three points. (i) The size of the respective case-study (Sioux-Falls) does not invoke tangible differences in the total travel time, (ii) In contrast to massive civil engineering projects such as building new bridges, new roads, etc. which can be called as hard schemes, contraflow can be considered as a soft scheme in traffic management. For example, the force of several prodigious road construction projects would result in one or two percent decrease in the total travel time (Poorzahedy & Rouhani, 2007). With the same token, the changes in the total travel time when only contraflow schemes are involved are expected to be much less. (iii) This case-study is in fact purposely designed to provide a challenging testbed for the proposed methodology in the sense that with such narrow marginal differences (of the values of the objective function) finding the global optimal solutions will not be a no-brainer task.

As can be seen in the table, the value of the objective function (4th column of the table) decreases till it reaches to 3919.353 (at the budget value of 2) and it remains constant all the way to the last budget, (i.e., 2, 3, …, 10). It means that in the optimal scenario one-way solution, there exist only two (two-way) roads to be turned to one-way roads. Note that the in the above setup, a scenario of the budget of say X means that the maximum number of two-way roads that can be turned to one-way is X. For example, in the scenario of the budget value of 10, though it is possible to have 10 roads turned to one-way, in the optimal scenarios, 2 (out of 10 possible) roads are found to become one-way. This setup would challenge the capability of the proposed methodology to find the global optimal solution in both tight and loose budget situations.

Comparing the strings of the optimal scenario of the budget of 1 unit to that of the budget of 2 units shows that the direction of the one-way road (4,11) is reversed. In other words, the one-way link (11, 4) in the optimal scenario of the budget of 1 unit switched to opposite direction in the budget of 2 units, showing the sensitivity of the outcome to the budget factors. The budget is a decisive factor in the contraflow problem such that a tiny change in the budget ought to change the roads' directional settings. Nevertheless, there exists one more one-way link (i.e. (6,2)) in the optimal one-way scenario of the budget of 2 units. In Fig. 2, traffic flows of two optimal scenarios corresponding to the budgets of 1 and 2 units are shown. As can be seen in Table 1, the value of the objective function (the 4th column) decreases till it reaches to 3919.353 (at the budget value of 2) and it remains constant all the way to



List of candidate roads, ordered to be shown in a binary string

no	1	2	3	4	5	6	7	8	9	10
i	**1**	**2**	**3**	**6**	**8**	**5**	**9**	**4**	**11**	**10**
j	**3**	**6**	**12**	**8**	**16**	**9**	**10**	**11**	**14**	**15**

i and j are node number

Fig. 1. Sioux-Falls network (The numbers on the links are the respective traffic flow. They are originated from solving the traffic assignment problem (TAP) for the existing scenario (i.e. no one-way scenario)).

Table 1
Sioux-Falls case study, the numerical results.

Budget	Global optimal solution			Solution found by the ML-O algorithm		
	A string of the scenario	Solution space (total number of possible combinations)	Value of the objective function	Rank of the solution found	Iteration at which the best solution was found	CPU time (sec)
0	0000000000*	1	3921.741	1	1	2
1	0000000200	21	3919.675	1	16	38
2	0200000100	201	3919.353	1	9	25
3	0200000100	1161	3919.353	1	24	55
4	0200000100	4521	3919.353	1	38	82
5	0200000100	12585	3919.353	1	36	78
6	0200000100	26025	3919.353	1	32	70
7	0200000100	41385	3919.353	1	33	72
8	0200000100	52905	3919.353	3**	50	107
9	0200000100	58025	3919.353	1	33	72
10	0200000100	59049	3919.353	1	26	58

* This is a succinct way of denoting a one-way scenario as follows: the candidates are ordered as per their assigned number in Fig. 1, if a two-way road remains the same (no change to the road's direction) it is assigned the value of zero, if a two-way road (i,j) is assigned 1, it means the road has become one way from i to j (e.g.,see candidate (4,11), the third from end, in scenarios of the budgets 2–10), if a two-way road (i,j) is assigned 2, it means the road has become one way from j to i.
** The string of the scenario is '0100000200' and the value of the objective function is 3919.469.

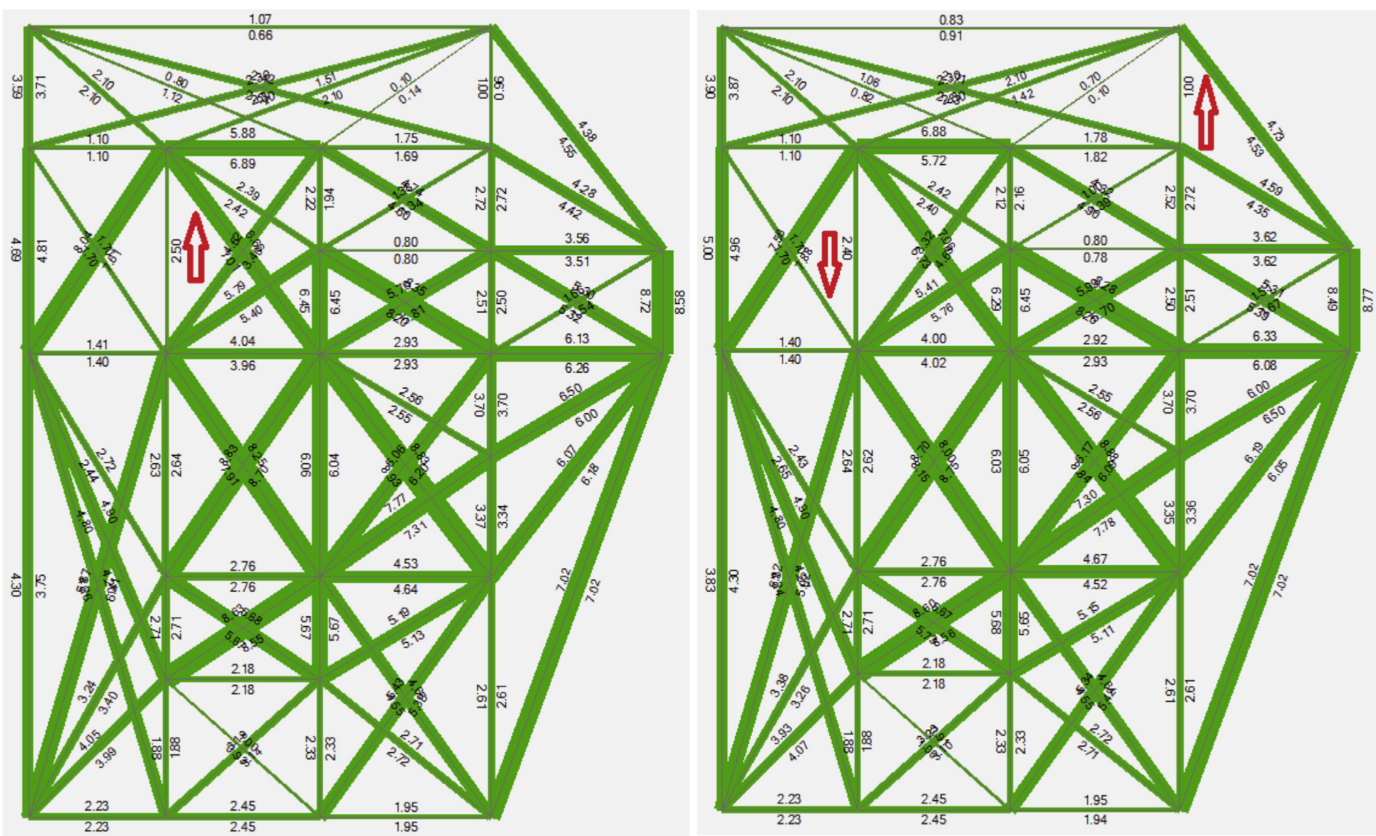


Fig. 2. Sioux-Falls case study, two optimal one-way scenarios.

the last budget, (i.e., 2, 3, …, 10). It means that in the optimal one-way scenario, there exist only two (two-way) roads to be turned to one-way roads. Note that in the above setup, a scenario of the budget of X means that the maximum number of two-way roads that can be turned to one-way is X. For example, in the scenario of the budget value of 10, though we could have 10 roads turned to one-way, in the optimal scenarios, only 2 (out of 10 possible) roads are found to become one-way.

Moreover, as can be seen in Fig. 2, except the areas surrounding the one-way roads, the sheer size of traffic flows across the network in both scenarios does change significantly. This vindicates the local (and not necessarily global) impacts of such schemes (let us call them soft schemes) to address some locally-intense traffic issues such as traffic gridlock in peak hours at the CBDs, or traffic control of major events such as sport games, evacuations etc.

As noted before a commensurate maximum number of iterations is 300 (10 times the number of binary variables, 30). To make it a challenging case, the proposed ML-O algorithm is run only for a maximum of 50 iterations for various budget levels and it stops when the global optimal solutions are found.

The results are reported in Table 1 (to the right of the table, the grayed color columns). As can be seen from the table, in all the budget levels except budget of 8 units, the algorithm manages to find the global solutions in less than 1.5 minutes. Given the size

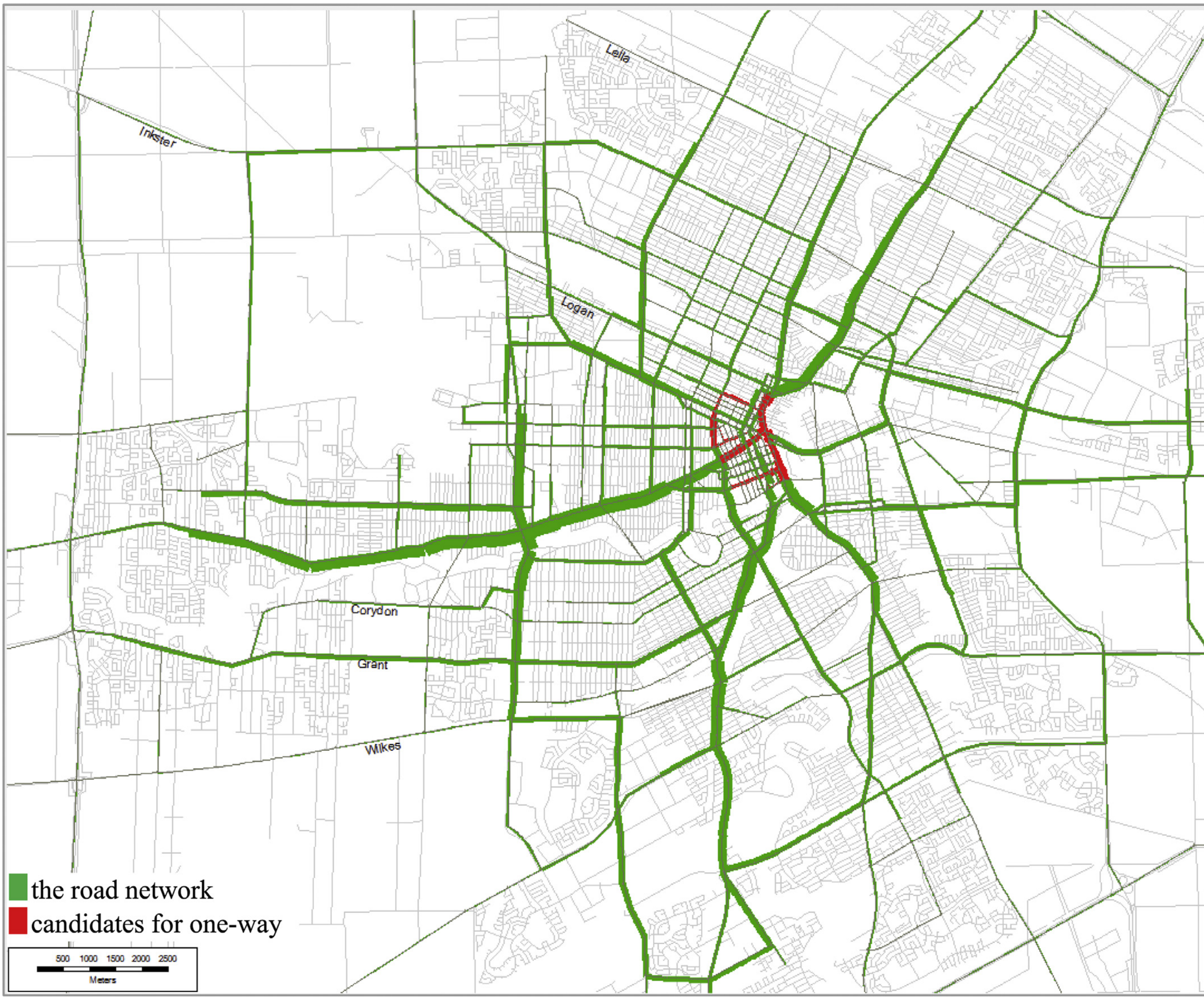


Fig. 3. Winnipeg case study, road network and candidates roads of the CBD (the thickness of the roads indicates the relative size of their respective traffic volumes).

of the solution space (number of possible combinations at different budget levels), the algorithm manages to find globally optimal solutions in rather few iterations. For the budget level of 8, though the global optimal solution was not found in the first 50 iterations, the third best solution was found.

5.2. Winnipeg

The road network of Winnipeg consists of 154 traffic analysis zones, 944 nodes, and 3383 directional links. The travel demand is a 154 by 154 matrix of 56,219 hourly trips in the morning peak hour. In transport, travel demand is considered as the rate of (hourly) trips originated at an origin and heading to a destination, whereas, zones represent the origins and destinations. Therefore, the travel demand can be denoted as a square matrix of order 154 (Sheffi, 1985).

The Winnipeg case-study is designed as a traffic management case, in which the aim is to provide easy access to the central business district (CBD) enclosing vital premises such as universities, hospitals, commercial centers, police stations, banks, fire stations etc. In other words, the travel demand used in the case-study pertains the city's daily morning trips. Similarly, one can come up with totally different scenarios just by replacing the travel demand with that of intended scenarios such as evening travel demand. By the same token, by replacing the travel demand with a post-disaster evacuation travel demand (i.e. how many people are to be transferred from their home or offices to shelter locations), the case study becomes an evacuation planning scenario. In all these scenarios, for evaluation purposes as a practical scale, what is important is the number of roads, nodes as well as the dimension of the travel demand matrix. We select 83 two-way roads as candidates from the CBD as shown red-colored in Fig. 3 (the thickness shows the intensity of the traffic flows). For details of the candidates, we refer to the GitHub link (Bagloee, 2018). It is important to note that cardinality of the candidate set (83) is a large number which makes the case-study more challenging (given the cardinality of the candidate set (83) the number of binary variables becomes 249 (i.e. 3*83) which results in an astronomically large solution space enclosing 2^{249} solution points).

Given the type of the BPR functions (the rods' travel time function) which is in the unit of minutes, the unit of the objective function (i.e. the total travel time spent on the network by all vehicles) is also in minute. Since the total number of candidates is 83, the total number of binary decision variables becomes 249=3*83

Fig. 4. Winnipeg case study, the CBD, traffic flow of the best contraflow (one-way) scenarios (the thickness of the roads indicates the relative size of their respective traffic volumes, the numbers indicate the traffic volumes in hourly rate).

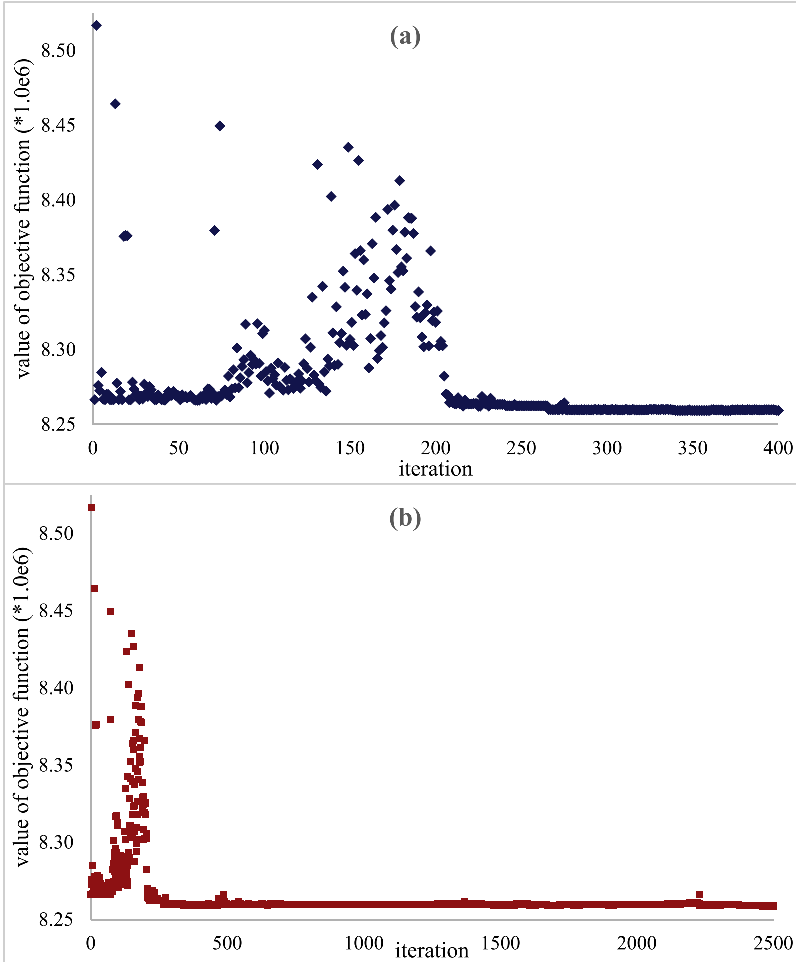


Fig. 5. Winnipeg case study, variations of the value of the objective function over 2500 iterations.

(note that each candidate is associated with three binary variables $y_{ij}^1, y_{ij}^2, y_{ij}^3$). Hence, following the rule of thumb discussed before, the total number of iteration is set to be 2500 > 249*10. The algorithm is then run while setting the budget to infinity to find the best possible contraflow scenario irrespective of any budget constraint.

In the end, the best contraflow scenario consists of 15 (out of 83 candidates) two-way roads turned to one-way which is shown in Fig. 4. As can be seen, this is a contraflow scheme to ease traffic circulation within the CBD during the morning peak hour. The significance of this scenario is to turn a main road for a significant length (550 m), consisting of 3 out of 15 segments to a one-way road (see the road marked with an straight arrow in Fig. 4). Nevertheless, there also exist 12 more segments scattered across the CBD turned to one-way roads. It is also important to note that a clear majority of the candidate roads remain intact which shows the merit of the proposed algorithm to find a few roads amongst hundreds. As a result, the proposed algorithm managed to create a cycle flow (as shown in the figure) which obviates traffic conflicts and helps a smooth and uninterrupted traffic circulation.

The values of the objective function over successive iterations are depicted in Fig. 5. The convergence profile shown in Fig. 5 seems strange in the sense that it is chaotic in the beginning and then stabilizes in the later iterations. To this end, it is worth noting that the proposed algorithm is a heuristic (and not exact) method based on the concept of training borrowed from machine learning. In early iterations, as expected, when the training is being consolidated, the objective function varies drastically. However, as the algorithm proceeds further, these variations stabilize and tend to converge as shown in Fig. 5(b). What is important to note is that, though the ML-O managed to find all the optimal solutions of the Sioux-Falls example, as a heuristic method, it generally does not guarantee the reserving of the optimal solutions. Facing with large-scale bilevel and NP-hard problems, what is expected from a heuristic method is to provide “good solutions” at reasonable and affordable computational time.

Fig. 5 can also provide a supportive argument of the termination criterion adopted in the ML-O. It can be argued that the ML-O implicitly considers two termination criteria, one based on the convergence rate of the value of the objective functions and the other one is based on a maximum number of iterations. The latter is a conservative criterion in the sense that the former criterion is also embedded in. In other words, as shown in Fig. 5, the gap between the values of the objective functions in successive iterations in the final stages of the computation is minuscule. However, in most of the (meta)heuristic algorithms including the Genetic Algorithm, it is the number of iterations that decides when to terminate the computation.

The total computation time (CPU time) of 2500 iterations is around 6.40 hours. The improvement pace of the value of the objective function as well as the gradual growth of the CPU time over successive iterations is sketched in Fig. 6. As can be seen, a clear

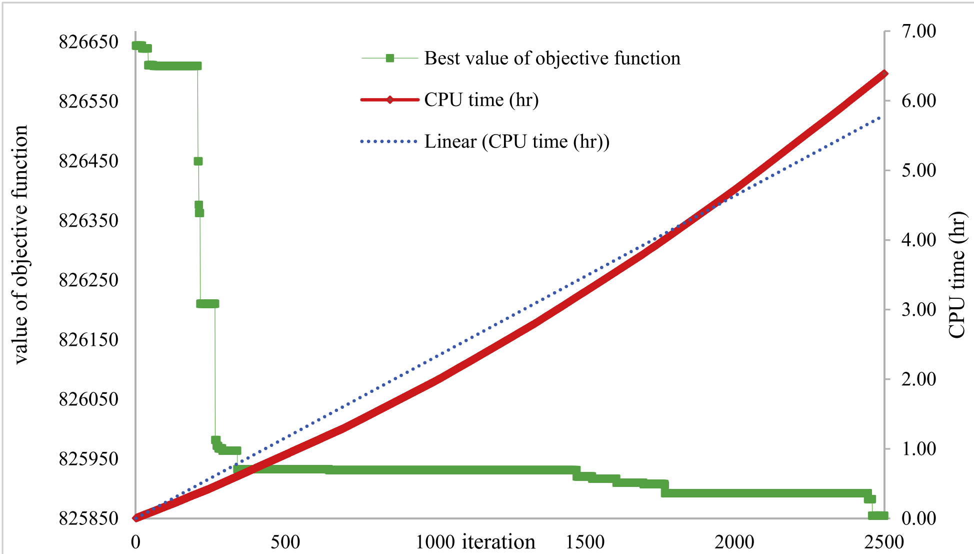


Fig. 6. Winnipeg case study, best solution founds versus computational time over 2500 iterations.

majority of the improvement (in the value of the objective function) is gained in early iterations (say the first 500 iterations). The algorithm starts with the value of 826,643 minutes (corresponding to the existing do-nothing scenario) and delivers a scenario with the total travel time of 825,854 minutes which is equivalent to 0.1% improvement across the entire network including the trips pertaining to the CBD. The fact that by changing the directions of a few roads, traffic across the road networks improves (and does not deteriorate) is worthy of note. However, a question to ask is: is this improvement (0.1%) negligible? To answer this question, it is important to compare a contraflow project which is relatively cheap (affordable) as well as easy and quick to implement, with massive investment in the road construction projects such as new roads, tunnels, bridges, spaghetti interchanges. It is empirically proven that in reality, these massive road construction projects are usually associated with only a few percent improvements in the total traverse time (see Table 6 in (Poorzahedy & Rouhani, 2007) and (Bagloee et al., 2017)).

Hence, compared to the capital and labor-intensive road construction projects, a contraflow strategy as an affordable and quick scheme can be regarded as an effective and affordable way to alleviate traffic congestion, especially in dense CBD areas. As note before, the main advantage of the contraflow schemes is to reduce traffic conflicts which invokes a detailed microsimulation modeling. Perhaps, a combined macro (this study) and micro simulation methodology can provide a better analysis of the contraflow schemes. As discussed above, microsimulation and dynamic assignment methods are computationally expensive, hence, by a macro modeling method (this study), one can identify a much fewer roads found out of a much larger area. These fewer roads can then be passed on to a microsimulation model for further analysis.

In large-scale applications, it is important to monitor the CPU time. As shown in Fig. 6, the gradual growth of the CPU time over successive iteration is almost linear. In other words, despite accumulating more constraints in the CP-ILP (see Constraint (10)), the additional computational burden is not significant. Therefore, the proposed methodology is tailored to the real-life scenarios, in the sense that the incremental computational time in successive iterations conforms to a linear trend.

This research is one of the few studies attempted to address the contraflow for a large-sized network as a bilevel and NP-hard problem. The contraflow scheme can be used as an effective traffic control measure by traffic authorities and practitioners for which 6 hours computational time is not an issue. In fact, nowadays, given the size of the traffic models of metropolitan cities, an overnight runtime is reasonable for practitioners (Bliemer, Raadsen, de Romph, & Smits, 2013).

In post-disaster applications when it is the race against time, one can terminate the algorithm with a few iterations only after the chaotic training part which is identical to the number of candidate roads (i.e. $|A'|$). As shown in Fig. 5, the algorithm quickly converges to some good solutions when it passes the early chaotic training segment (as discussed above), and the rest of the iterations are the efforts to find a better solution. In other words, a premature termination does not have a detrimental effect on the outcome. Moreover, we used a normal desktop computer, however, in such circumstances, one can employ higher computational technologies which results in much lower computational time.

For emergency evacuation, the computation time can be further reduced using powerful computers and parallel computation. Solving the integer program (CP-ILP) and the traffic assignment are main sources of the computation and they can be made parallel (GAMS, 2014; INRO, 2017).

It is also worthwhile to investigate the fitness of the linear regression model as the algorithm proceeds to further iterations. To this end, Fig. 7 depicts the changes of the R-squared values of the linear regression model versus the values of the objective function of the best solution found (note that, the R-squared values of the iterations less than 250 are not reported. That is because the number of training records is less than the number of independent variables, hence it is pointless to report their outcomes. As evidenced by the figure, the regression model quickly gets fitted to the training records. As the number of iterations increases (i.e. more training data) the R-squared values increase too. However, the pace of the growth diminishes at iteration 1250 onward. It is also important to notice the correlation of the R-squared values versus the values of the objective function of the best solution found. What is clear is that, no matter how good the linear regression model might be (as is the case after iteration 1250) the algorithm still needs to carry on further (i.e. more iterations) to find much better solutions as found at iteration 2460. Consequently,

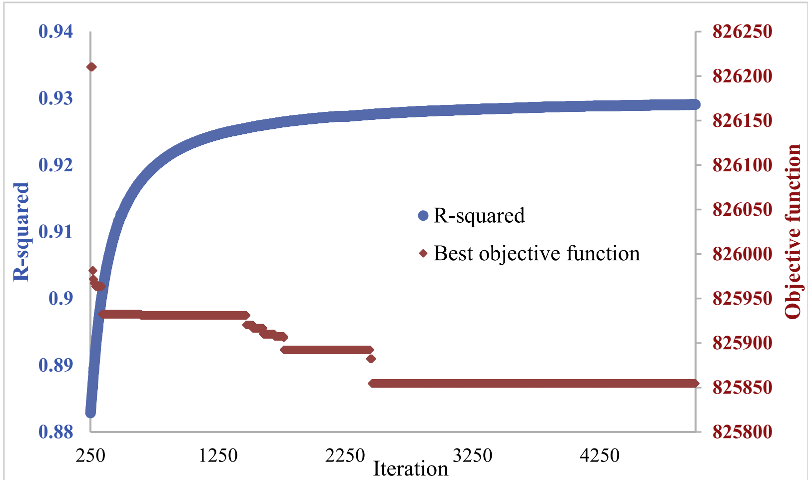


Fig. 7. Regression training (R-squared) versus the best objective function found.

two important conclusions can be drawn. (i) The algorithm can find a well-rounded fit for the linear regression model. (ii) Tracking down the regression fitness is not a good clue to decide to terminate the algorithm.

6. Conclusion

The contraflow problem (CP) as a technique for traffic management and emergency evacuations was addressed in this study. The main idea behind the contraflow is to change roads directions to provide better traffic circulation. The CP can be regarded as an extension of the well-known Network Design Problem (NDP) for which there exists a plethora of research. The authors formulated the contraflow as a bilevel optimization problem to minimize the total travel time in the upper level while accounting for the drivers' route choice in the lower level (as a traffic assignment problem). The bilevel problems are proven to be NP-hard, that is, as the size of the road networks (number of roads) increase the problem becomes computationally prohibitive. The authors in this study took on a challenging job of addressing the contraflow for real-life examples. Generally speaking, for the NDPs and CPs in particular, given these computational complexities, analytically exact methods are not scalable to the real size examples. There exist myriads of (meta) heuristic methods proposed to solve bilevel NDPs such as Genetic Algorithms, Simulated Annealing, Ant Colony etc. Alternatively, a heuristic method aiming to find good solutions in an affordable epoch of time is used. To this end, the authors use a hybrid heuristic method based on a supervised technique borrowed from the machine-learning and an optimization algorithm. The methodology was coded as a user-friendly software while synchronized with GAMS (to solve the integer optimization problems), MATLAB (for machine learning), EMME 3 (to solve the traffic assignment problems), MS-Access (as a database) and Excel (as an interface). The proposed methodology was numerically tested using two case studies a medium-sized network (Sioux-Falls) and a large-sized network (Winnipeg). The results were found promising, to the extent, the algorithm managed to find optimal solutions for Sioux-Falls and displayed efficient convergence when applied to Winnipeg. Comparative analysis shows that the proposed hybrid machine learning method by far outperforms some of the metaheuristic algorithms.

- An intuitive bilevel formulation for the contraflow problem (CP) was proposed.
- A machine-learning solution algorithm was proposed to solve the CP.
- The solution algorithm was tailored to large-sized networks, as the computational time was found to be of a linear order (and not exponential).
- Compared to some alternative solution algorithms (e.g. metaheuristic methods) the proposed hybrid machine-learning method was found more fit to the CP.
- The proposed methodology considers the traffic simulation part (i.e., the traffic assignment) as a black-box, which can then be easily replaced with other alternatives such as a detailed meso or micro traffic simulation model.
- To further expedite the computation, the proposed methodology is structured in a way that the algorithms can be executed in multiple cores (i.e. parallel computation).

There exist some avenues to improve the proposed methodology. In an emergency evacuation, uncertainty in different aspects is a significant concern which is largely overlooked. Extending this methodology to a stochastic formulation is a worthwhile effort to enhance the realism of the model. With the same token, the sensitivity of the parameters (such as the budget) to the outcomes needs to be further investigated, for which one way is to resort to a robust optimization method. In the interest of computation time, the authors utilized the user-equilibrium traffic flow as a traffic simulation model. In fluid situations, such as emergency evacuation, it is a worthwhile endeavor to include a computationally efficient dynamic traffic model into the methodology. The idea of contraflow can be further improved if it is unified with other network management measure such as intersections' traffic signal timing as well as turning movements design. In evacuation applications, communication with evacuees and broadcasting changes of the transport infrastructure should also be integrated into the ontology of evacuation (Onorati, Malizia, Diaz, & Aedo, 2014). The concept of the contraflow can also be investigated for indoor evacuation (Wagner & Agrawal, 2014). To this end, there is a growing body of research and technology concerning indoor evacuation guidance using a variety of means including smart phones, the internet of things, smart signages and lighting (Bernardini, Azzolini, D'Orazio, & Quagliarini, 2016; Cheng et al., 2017; Fujihara & Yanagizawa, 2015; Ohta et al., 2015). The contraflow problem in this study was solved based on the minimization of the total traverse time as the only objective function. However, it is also an endeavor to expand the model to a multi-objective optimization which has more application in emergency evacuations (Chang, Wu, Lee, & Shen, 2014).

People's psychology and their behavior in disaster events and panic conditions as well as the effects of emotional intelligence and empathy have been topics of extensive research (Kang, Lindell, & Prater, 2007; Lindell, 2008; Lindell & Prater, 2007; Riad, Norris, & Ruback, 1999).

It appears, the complex and somewhat bewildering phenomenon of people's erratic behavior (e.g. to evacuating from a dangerous situation) is influenced by a combination of individual characteristics and basic social psychological processes such as risk perception, social influence, and access to resources. (Riad et al., 1999). Delineating the weights of these factors will help authorities to effectively plan for evacuation operations which desrve further research. Beside, social scientists' research on population's behavior has been loosely integrated with transportation engineers' development of evacuation models (Lindell & Prater, 2007) which warrants an interesting and yet timing line of research.

Furthermore, it was postulated that when it comes to people's evacuation behavior, there is no difference between natural and man-made disasters. In both, we assume that using modern technologies (e.g. smart phone, radio, variable message sign etc.) as well as law enforcement forces, when an evacuation plan (or a traffic management scenario) is decided, people would largely comply with. Nevertheless, investigating true nature of people's behavior in response to evacuation plans in anthropogenic and natural disasters is an interesting subject for further research

Author contributions

S.A.B. and K.H.J conceived of the presented idea. S.A.B developed the theory and performed the computations. K.H.J verified the analytical methods. M.A. helped coding the algorithm. All authors discussed the results and contributed to the final manuscript.

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