Eco-routing: An Ant Colony based Approach

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Abstract: Global warming, environmental pollution, and fuel shortage are currently major worldwide challenges. Eco-routing is one of several tools that attempt to address this challenge by minimizing network-wide vehicle fuel consumption and emission levels. Eco-routing systems select the most environmentally friendly route. The subpopulation feedback eco-routing (SPF-ECO) algorithm that is implemented in the INTEGRATION software can produce a reduction in fuel consumption levels by approximately 17%. However, in some cases, due to delayed updates or the lack for updates, its performance degrades. In this paper, we propose the ant colony based eco-routing technique (ACO-ECO), which is a novel feedback eco-routing and cost updating algorithm to overcome these shortcomings. In the ACO-ECO algorithm, real-time performance measures on various roadway links are shared. Vehicles build their minimum path routes using the latest real-time information to minimize their fuel consumption and emission levels. ACO-ECO is also able to capture randomness in route selection, pheromone updating, and pheromone evaporation. The results show that the ACO-ECO algorithm and SPF-ECO have similar performances in normal cases. However, in the case of link blocking, the ACO-ECO algorithm reduces the network-wide fuel consumption and CO_2 emission levels in the range of 2.3% to 6.0%. It also reduces the average trip time by approximately 3.6% to 14.0%.

1 INTRODUCTION

The environmental and economic impact of the transportation sector has necessitated research in recent years because the transportation sector is an important source of the major current challenges, including: global warming, energy and fuel shortage, and environmental pollution. In 2008, the U.S. Department of Energy mentioned in (U.S. Dept. Energy 2008) that approximately 30% of the fuel consumption in the U.S. is consumed by vehicles moving on the roadways. In addition, about one-third of the U.S. carbon dioxide (CO_2) emissions comes from vehicles (U.S. E.P Agency 2006). The 2011 McKinsey Global Institute report estimated savings of “about $600 billion annually by 2020” in terms of fuel and time saved by helping vehicles avoid congestion and reduce idling at red lights or left turns.

From the drivers’ perspective, drivers usually select routes that minimize their costs such as travel time or travel distance. However, the minimum time or distance routes do not necessarily minimize the fuel consumption or emission levels (Barth, Boriboonsomsin et al. 2007, Ahn and Rakha 2008). There are many cases where the minimum time routes result in higher fuel consumption levels such as high-speed routes; despite the time reduction that could be achieved, the higher speed routes may produce higher fuel consumption levels due to the higher vehicle speeds, route grades or longer distance. Also, shorter distance routes can result in higher fuel consumption if the speed is too low or if the route has many intersections that result in numerous deceleration and acceleration manoeuvres. Selecting the minimum time or minimum distance routes is simple compared to finding the minimum fuel consumption routes. The fuel consumption depends on many parameters such as distance, travel time, route grades, congestion level, vehicle characteristics, and the driving behaviour.

Researchers have proposed several models for the estimation of vehicle fuel consumption and emission levels. These models can be classified into two classes; macroscopic models (Brzezinski 1999, ARB 2007) and microscopic models (Barth 2000, Rakha, Ahn et al. 2004). In macroscopic models, the average link speeds are used to estimate the fuel consumption and emission levels for each link. This class is

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characterized by its simplicity but has a limited accuracy because it ignores the speed and the acceleration impacts on fuel consumption levels. Meanwhile, microscopic models overcome this limitation using instantaneous speed and acceleration levels to estimate the fuel consumption and emission levels. Consequently, microscopic models provide higher accuracy at the cost of model complexity.

Eco-routing (Ericsson, Larsson et al. 2006) was developed to select the route that minimizes vehicle fuel consumption levels between an origin and destination. In a feedback system, Eco-routing depends on the vehicle and route characteristics as well as its ability to report this information to a traffic management center (TMC) that updates the routing information, rebuilds the routes, and sends the new routes to vehicles traversing the network.

Eco-routing is a promising navigation technique because it results in a significant reduction in fuel consumption and emission levels. However, through some improvements, the Eco-routing system can be further enhanced to produce additional fuel consumption and emission savings.

In this paper, we first study the Eco-routing performance and show that in some cases its performance may not be optimum. Subsequently, based on this, we propose an ant colony Eco-routing (ACO-ECO) algorithm that employs the ant colony optimization algorithms (Dorigo and Birattari 2010). Due to the major differences between the ant colony and the transportation network, the ant colony algorithms are not directly applied to select the best routes, however, they are used to optimize the route selection process by optimizing the route selection updating. Finally, we compare the proposed approach to the subpopulation feedback Eco-routing algorithm (SPF-ECO) (Rakha, Ahn et al. 2012).

The remainder of this paper is organized as follows. An overview of the Eco-routing literature and the subpopulation feedback assignment Eco-routing (SPF-ECO) algorithm is introduced. This is followed by outlining the main problems with the SPF-ECO algorithm. Subsequently, an overview of the ant colony optimization is presented. After that, the proposed approach (ACO-ECO) is described. Subsequently, the simulation results that compare the ACO-ECO to the SPF-ECO are presented and discussed. Finally, the study conclusions are presented together with recommendations for further research.

2 ECO-ROUTING LITERATURE

In 2006, Ericsson *et al*. proposed the Eco-routing in (Ericsson, Larsson et al. 2006) where they presented a comprehensive study that provides optimal route choices for lowest fuel consumption. The fuel consumption measurements are made through the extensive deployment of sensing devices in the street network in the city of Lund, in Sweden. This study showed that about 46% of the trips were not made on the most fuel-efficient route. And approximately 8% of the fuel consumption could be saved on average using the most fuel-efficient routes. In 2007, Barth *et al*. (Barth, Boriboonsomsin et al. 2007) combined sophisticated mobile-source energy and emission models with route minimization algorithms to develop navigation techniques that minimize energy consumption and pollutant emissions. They developed a set of cost functions that include the fuel consumption and the emission levels for the road links. In 2007, Ahn and Rakha (Ahn and Rakha 2007) showed the importance of route selection on the fuel consumption and environmental pollution reduction, by demonstrating through field tests that an emission and energy optimized traffic assignment could reduce CO_2 emissions by 14 to 18%, and fuel consumption by 17 to 25% over the standard user equilibrium and system optimum assignment. Later in 2012, Rakha *et al*. (Rakha, Ahn et al. 2012), introduced a stochastic, multi-class, dynamic traffic assignment framework for simulating Eco-routing using the INTEGRATION software (Rakha Last Access Feb. 2016). They demonstrated that fuel savings of approximately 15% using two scenarios were achievable. In (Boriboonsomsin, Barth et al. 2012), the authors developed an Eco-routing navigation system that selects the fuel-efficient routes based on both historical and real-time traffic information.

2.1 Subpopulation Feedback Eco-routing

In this section, we will describe in details the subpopulation feedback assignment Eco-Routing SPF-ECO (Rakha, Ahn et al. 2012) implemented in the INTEGRATION software. INTEGRATION uses the VT-Micro model (Rakha, Ahn et al. 2004) for calculating the fuel consumption rate $F(t)$ in L/s for each vehicle as shown in Equation (1).

$$F(t) = \begin{cases} exp\left(\sum_{i=1}^{3}\sum_{j=1}^{3} L_{i,j}\, v^i\, a^j\right) & if\ \ a \geq 0 \\ exp\left(\sum_{i=1}^{3}\sum_{j=1}^{3} M_{i,j}\, v^i\, a^j\right) & if\ \ a < 0 \end{cases} \quad (1)$$

Here $L_{i,j}$ are model regression coefficients at speed exponent i and acceleration exponent j, $M_{i,j}$ are model regression coefficients at speed exponent i and acceleration exponent j, v is the instantaneous vehicle speed in (km/h), and a is the instantaneous vehicle acceleration (km/h/s).

An important characteristic of INTEGRATION is its time granularity which is a deci-second resolution. This granularity enables it to accurately calculate the fuel consumption and emissions based on instantaneous speed and acceleration levels.

In SPF-ECO, when the vehicle enters a new link. The vehicle's fuel consumption and emission levels are reset to zero for the new link. Subsequently, the SPF-ECO algorithm periodically calculates the fuel consumption and emissions for each vehicle using Equation (1). For each vehicle, the estimated fuel consumption and emission levels are accumulated until the vehicle traverses the link. When a vehicle leaves a link, it submits its fuel consumption cost for this link to the traffic management center (TMC), which updates the link fuel consumption using some smoothing techniques. Subsequently, INTEGRATION periodically rebuilds the routes for each origin-destination pair at a frequency specified by the user. Subsequently, vehicles use the latest paths when looking identifying the next link along the route. This mechanism has three main shortcomings that are discussed in this section.

2.1.1 Fixed Cost for Empty Links

Assume that a link L_i was loaded with a high traffic flow that resulted in congestion on this link. This congestion will result in a lower speed and increasing the acceleration/deceleration noise. Consequently, increasing the fuel consumption and emission levels on this link. At a certain time, the SPF-ECO system will re-route vehicles to another route that reduces the route cost. Since the vehicles on L_i have been exposed to the congestion, the link fuel consumption will be very high after these vehicles leave the link. As the system re-routes vehicles to other routes, the link will not be loaded by vehicles until the routing information changes. Consequently, the cost of L_i will continue to be high while it is actually decreasing. This lag in the system is typical of any feedback control system and will result in vehicles using sub-optimal routes. Consequently, increasing the network-wide fuel consumption levels.

2.1.2 Fixed Cost for Blocked Links

A reverse situation can take place in case of blocking a link (for example due to an incident). In this case the vehicles that were not blocked will have a low fuel consumption level, and will report it when leaving the link. The SPF-ECO will maintain a low cost for this link as long as the link is blocked since there is no vehicle leaving the link to update the information on this link. Consequently, the SPF-ECO will continue to use this route and load more vehicles to this link resulting in higher fuel consumption and emission levels.

2.1.3 Delayed Updates

The third point is that the updates are only sent when a vehicle leaves a link. For long links and/or low-speed links, the link travel time is relatively long. Consequently, the information used to update the SPF-ECO routing might be obsolete and may not reflect the current state of the link. This inaccurate routing information might result in incorrect routing decisions and hence increase the fuel consumption level.

In the proposed approach, we solve these problems by utilizing ant colony techniques to update the link cost function (the fuel consumption level in this application).

3 ANT COLONY OPTIMIZATION

Ant colony optimization (Dorigo and Birattari 2010) is a branch of the larger field of swarm intelligence (Blum and Li 2008). Swarm intelligence studies the behavioural patterns of social insects such as bees, termites, and ants in order to simulate these processes. Ant colony optimization is a meta-heuristic iterative technique inspired from the foraging behaviour of some ant species. In the ant colony, ants walking to and from a food source deposit a substance called pheromone on the ground. In this way, ants mark the path to be followed by other members of the colony. The shorter the path, the higher the pheromone on that route, and consequently, the preferable this route is. The other ant colony members perceive the presence of pheromone and tend to follow paths where pheromone concentration is higher. Ant colony optimization exploits a similar mechanism for solving some optimization problems.

In this paper, we use the same ant colony concept to optimize the fuel consumption and emission cost for a transportation network. Vehicles are employed as artificial ants, the pheromone is considered to be the inverse of the fuel consumption cost for each link. Each artificial ant periodically deposits the pheromone by updating the fuel consumption cost for the link it is traversing.

There are many variants of ant colony optimization. However, all of them share the same idea described earlier. The main steps in each iteration are: 1) construct the solutions, 2) conduct an optional local search step, and 3) update pheromones. The ant colony system does not specify how these three steps are scheduled and synchronized, the system leaves these decisions to the algorithm designer (Blum 2005). In the solution construction step, artificial ants construct a feasible solution and add it to the solution space. The system starts with an empty solution space, the ants start at the nest, and each ant probabilistically chooses a solution e_i between a set of paths $\{e_1, e_2, \dots e_k\}$ to reach the food source. To choose between these paths, each ant uses the probability P_i computed in Equation (2).

$$P_i = \frac{\varphi}{\sum_{j=1}^{k} \varphi_j} \tag{2}$$

Where φ_i is the amount of pheromone on path e_i. This probabilistic behavior for route selection guarantees the exploration of more feasible solutions and avoids converging to local ones.

The pheromone updating takes place while the ants are moving, where they deposit the pheromone on their paths. Also, as time passes, the pheromone evaporates based on an evaporation factor ρ. Subsequently, after each iteration, the phenome is updated according to Equation (3).

$$\varphi_i = (1 - \rho)\, \varphi_i + \sum_{j=1}^{m} \Delta\varphi_j \tag{3}$$

Where m is the number of ants that traverse a link, and $\Delta\varphi_j$ is the amount of pheromone deposited by ant j. After the solution construction and before the pheromone updating, the local search step can be carried out to improve the solution. This step is optional and problem specific.

In the proposed approach, we utilize these steps to achieve our objective of minimizing the fuel consumption and consequently the pollutant emissions.

4 ANT COLONY BASED ECO-ROUTING (ACO-ECO)

This section presents the proposed approach (ACO-ECO) and describes its operation in details. In ACO-ECO, the ant colony techniques will be applied to optimize the fuel consumption and emissions in the transportation network. The vehicles are the artificial ants, and the pheromone is the inverse of the fuel consumption. Because of the major differences between the ant colony system and the transportation network, we introduce some variations to ant colony techniques to tailor it to the specific application. The ACO-ECO uses a number of steps that are described here.

4.1 Initialization

This phase initializes the cost associated with the various links. Because initially the links are free, the cost of each link is initialized to the free flow speed fuel consumption using equation (1).

4.2 Route Construction

This phase starts directly after the initialization phase and is repeated periodically and was defined to be 60 seconds in this application. In this phase, the ACO-ECO builds the minimum path based on the cost of each link. When the vehicle leaves a route link, it searches the tree to find its next link.

The probabilistic route selection (introduced by Equation (2)) is an important mechanism in ant colony algorithms to search all the available routes. However, this mechanism as described in Equation (2) cannot be applied in vehicular route selection because it is not realistic. As mentioned earlier, drivers try to select routes that minimize their cost, while this probabilistic selection assigns a random route to each vehicle based on the route's pheromone level (route cost) relative to that for all other routes. Using this equation, and due to the randomness, a vehicle might be assigned a very high-cost route which is not realistic, and is not consistent with the driver behaviour when selecting routes. Consequently, it will result in a higher fuel consumption level. So, we use another technique to introduce some limited randomness into the route selection mechanism while maintaining the error within a given predefined margin. An error factor is configured for the network. This error factor (α) is used to add some error to the cost of the links, subsequently to the tree building and the route selection algorithms. The error value added to the link cost is a randomly selected point from the standard normal distribution $N(0, \sigma)$, where σ is the standard deviation and $\sigma = \alpha\,.\,link\_cost$. In this way, we have a grantee that 95.45% of the link costs are within $(1 \pm 2\alpha).\,link\_cost$. Which means that by controlling the error factor α we can control the randomness level within the route selection algorithm.

4.3 Pheromone Update

In this phase, two updating processes take place. Pheromone deposition where ants deposit pheromone to indirectly communicate the route preference to the following ants. And the pheromone evaporation, where the pheromone level on each link decays with time.

4.3.1 Pheromone Deposition

In the vehicular network, each vehicle sends the cost it experienced on a link to the TMC, and consequently, the link cost is updated in the routing algorithm. In the SPF-ECO, the vehicles only submit the link cost when leaving the link. The advantage of this method is the small number of updates being sent on the network and consequently the low network overhead. But on the other hand, it results in delayed updates and fixed cost for empty or blocked links as mentioned earlier.

In contrast to the SPF-ECO, the ACO-ECO overcomes these issues by enabling vehicles to submit multiple updates while traveling the link. These updates can be sent periodically either time-based or distance-based. Using time-based updating, the vehicles have a predefined maximum updating interval T. The vehicles should send their estimation for the link cost each T seconds. This cost updating method can control the number of updates that are sent over the network. However, it has an important drawback; for low speed links or blocked links, the vehicles will send many unnecessary updates. Another drawback is for short length links and/or high speed links, this time interval T may be longer than the link traversal time. Consequently, no updates would be sent for these links. This drawback can be overcome by setting T to a value that is shorter than the minimum link travel time in the network, however, this will result in many unnecessary updates for long links or low speed links.

Another way to submit the link cost updates is the distance based updating, where the vehicles should submit an update every distance D it traverses on the link. In contrast to the time based updating, the distance based method limits the number of updates for each link. But on the other hand, for blocked links, the updates will not be sent and consequently, the cost will be fixed for blocked links resulting in the same problem as the SPF-ECO algorithm.

Consequently, a compromise approach is proposed, which combines both the time- and distance-based updating to take advantage of the merits of each approach. Also, we used the end of the link updating where the vehicle sends an update when it leaves the link. To estimate the link fuel consumption, the ACO-ECO algorithm defines the maximum time interval T and the maximum distance D to report conditions. When any of these conditions is met, the vehicle submits a new update quantifying its estimation for the overall link cost, and then resetting its time and distance counter. To calculate the fuel it consumed, the ACO-ECO periodically estimates the fuel consumption rate using the VT-Micro model in Equation (1). And then uses Equation (4) to accumulate the total fuel consumed in the previous interval.

$$C = \sum_{t} F(t) \,.\, \Delta t \tag{4}$$

Where $F(t)$ is the VT-Micro model instantaneous fuel consumption rate, and Δt is the fuel consumption calculation interval which is typically 0.1 seconds in INTEGRATION. Whenever either T or D is reached, the ACO-ECO estimates the overall link fuel consumption C_l as shown in Equation (5).

$$C_l = \frac{C \,.\, L}{d} \tag{5}$$

Where d is the distance traveled in the previous period in meters $(d \leq D\,)$, and $L\ is$ the link length in meters. This calculation assumes that the conditions on the remainder of the link will continue as was observed by the vehicle.

4.3.2 Pheromone Evaporation

To overcome the fixed cost problem for empty links, the cost of these links must be updated when the TMC has not received updates for a period of time. In an ant colony, if no pheromone is deposited for a long time, the link pheromone level will decay towards zero due to the evaporation, this is an indication of the low preference for that route. In a transportation network, not receiving an update about a link for a long time, indicates that this link is empty. Consequently, the cost of this link must be updated toward the free flow speed cost (C_{ff_l}). So, in this case, the TMC updates the cost as follows. First, it finds the minimum updating interval ($\boldsymbol{\tau_l}$) for the link. This value is the minimum of three parameters; the updating interval (T), the link travel time at free-flow speed, and the updating interval in case of distance based updating. These parameters are shown in Equation (6). The rationale is that after receiving an update, the next vehicle will send an update in case of one of three situations; it reaches its updating interval T, it reaches its updating distance, or it ends the link.

$$\tau_l = min\left(T, \quad \frac{L_l}{S_{ff_l}}, \quad \frac{D}{S_{ff_l}}\right) \qquad (6)$$

Where T is the updating interval, D is the updating distance, $\boldsymbol{L_l}$ is the link length and $\boldsymbol{S_{ff_l}}$ is the free-flow speed of the link.

Subsequently, the ACO-ECO algorithm estimates the overall link cost C_l as shown in Equation (7). This evaporation technique results in exponential increasing or decreasing in the link cost towards the free-flow speed cost.

$$C_l = C_l - \frac{\Delta t}{\tau_l}\left(C_l - C_{ff_l}\right) \qquad (7)$$

Where C_{ff_l} is the free-flow speed fuel consumption estimate for the link, and Δt is the evaporation interval after which the evaporation process should be performed for the link cost if no updates were received.

5 SIMULATION RESULTS

In this section, we compare the proposed approach ACO-ECO to the SPF-ECO for different traffic rates using the INTEGRATION software (Rakha Last Access Feb. 2016). The network shown in Figure 1 is used for comparing the two approaches.

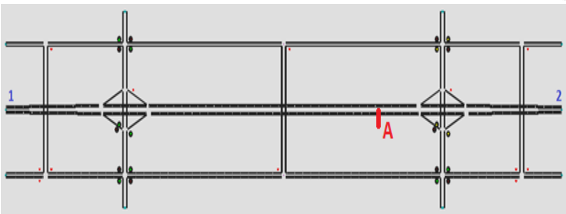

Figure 1: Road Network used in Simulation.

The network consists of 10 zones with the main highway (center horizontal road) between zone 1 and zone 2, and two arterial roads (side roads). The network size is 3.5 km x 1.5 km. The free-flow speeds are 110 and 60 km/h for the highway and arterial roads, respectively. The highway has 3 lanes in each direction while the other roads have only 2 lanes in each direction. Regarding the origin-destination traffic demands (O-D demands), we use 5 different scenarios, as shown in Table 1. The main traffic stream is the traffic between zone 1 and 2 for each direction, the side traffic streams are between each two other zone pairs. This traffic rate is generated for half an hour, and the simulation runs for 4500 seconds to ensure that all the vehicles complete their trips.

Table 1: Origin-Destination Traffic Demand Configuration.

	Main Demand (Veh/h)	Secondary Demand (Veh/h)	Total no. vehicles (Veh)
1	500	50	1600
2	1000	75	2650
3	1500	100	3700
4	2000	125	4750
5	2500	150	5800

The comparison is done in two cases; the normal operation (no incident) case where there is no link blocking, and in the case of blocking due to an incident (link blocking case). For each case, we run each traffic assignment technique (ACO-ECO, and SPF-ECO) 20 times with different seeds to consider the output variability due to randomization. This is repeated for each of the five O-D demand configurations. The error factor is set for both techniques to 1%. For the ACO-ECO parameters, the maximum update interval T is 180 seconds, and the maximum update distance D is 750 meter.

5.1 Normal Operation Scenarios

For the normal operation scenarios, the results show no significant differences between the ACO-ECO and the SPF-ECO for average fuel consumption levels, as shown in Figure 2. The figure also shows that as the traffic demand increases, the average fuel consumption and the average trip time increases due to the higher congestion levels. Moreover, the results show the same behaviour for the average trip time, the CO_2 and NO_x emissions levels, where ACO-ECO has no significant effect on any of them.

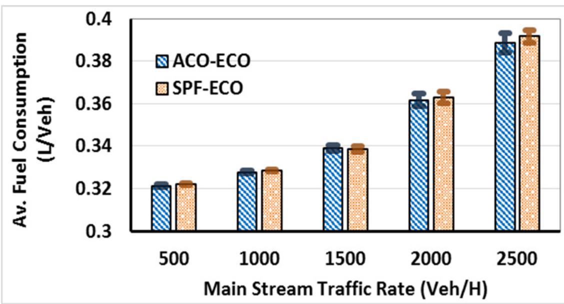

Figure 2: Average Fuel Consumption (L/Veh).

Regarding the CO emission, the ACO-ECO has a higher emission level as shown in Figure 3.

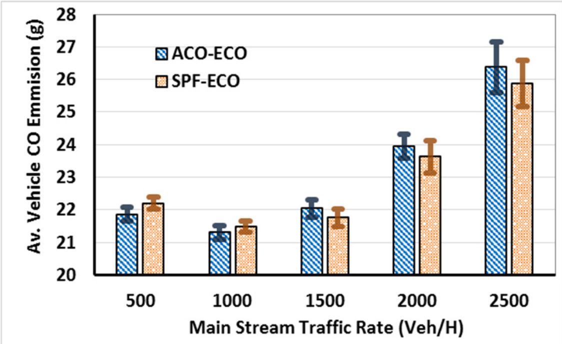

Figure 3: Average Vehicle CO Emission.

5.2 Incident Scenarios

To simulate the link blocking in the network, we configured an incident on the highway from zone 1 and 2 at point (A) marked in Figure 1, the incident does not affect the other direction from zone 2 to zone 1. This incident occurs 10 minutes after starting the simulation and blocks 50% of the highway (1.5 lanes) for 5 minutes. Then the blocking is reduced to 25% of the highway for the next 10 minutes, then the incident is completely removed and the highway works with its full capacity.

Figure 4 shows the fuel consumption in case of an incident. The figure demonstrates that the ACO-ECO algorithm reduces the average fuel consumption level for all traffic demands. The reduction ranges between 2.3% to 6% compared to the SPF-ECO.

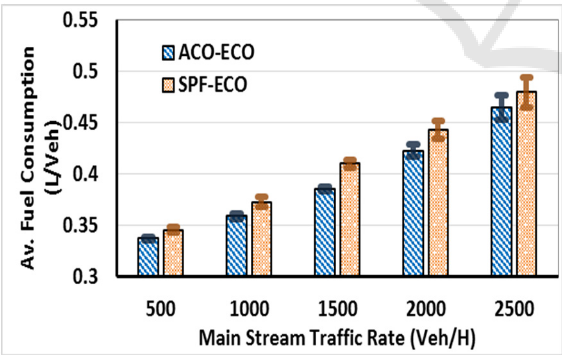

Figure 4: The Average Fuel for the Link Blocking Scenario.

These results show the ability of ACO-ECO to reduce the fuel consumption level and the trip time in addition to all the time-related measurements. ACO-ECO also succeeds in reducing the pollutant emissions in most cases.

Table 2 shows the percentage reduction attributed to the ACO-ECO for both fuel consumption, different emissions, and different time-related measurements. For instance, the fuel consumption is reduced by 6% in the moderate traffic scenario and this reduction ratio decreases as the traffic demand increases. This also applies for the CO_2 emissions and the time-related measurements. The reason is that as the traffic demand increases, the congestion increases and thus affects all the alternative routes, which limits the ACO-ECO ability to recover from the congestion.

To find the significance of the reduction made by ACO-ECO, analysis of variance (ANOVA) is employed to compare means of ACO-ECO to that of SPF-ECO.

The hypotheses are:-

- Null hypothesis: the means for both algorithms are equal ($H_0: \mu_1 = \mu_2$)
- The alternate hypothesis: the means are not equal ($H_a : \mu_1 \neq \mu_2$).

We applied this ANOVA for the fuel consumption results in the lowest traffic rate. Given this scenario has the lowest reduction in fuel consumption. The result shows that p-value is less than 0.0001. Which gives a strong evidence to reject the null hypothesis. And shows the significance of the reduction mad by the ACO-ECO. And, since the lowest reduction level is significant, we can conclude that the higher levels for other configuration are also significant.

Table 2 also, shows some rare cases where the some emissions increase in due to the use of ACO-ECO. For instance, CO and NOx emissions increased in case high traffic rates.

6 CONCLUSIONS

We propose an ACO-ECO traffic assignment technique that is inspired from the ant colony

Table 2: Percent of Reduction Made by ACO-ECO over SPF-ECO in case of Link Blocking.

Traffic rate	Fuel	CO_2	CO	HC	NO_x	Trip time	Stop delay	Accel. noise	Accel./Decel. delay
500	2.37	2.29	3.75	3.71	1.60	3.64	4.04	1.87	12.02
1000	3.72	3.86	1.05	1.73	0.91	8.83	19.04	4.90	21.97
1500	6.06	6.42	-1.51	0.38	0.24	14.98	27.68	5.28	25.43
2000	4.57	4.75	0.49	2.19	0.11	12.66	19.75	4.91	16.84
2500	3.09	3.32	-2.10	-0.58	-0.75	7.11	15.39	1.61	11.34

optimization algorithm. ACO-ECO attempts to enhance the SPF-ECO algorithm that is currently implemented in the INTEGRATION software. These enhancements include cases in which the links are blocked or no vehicles traverse the link. ACO-ECO employs the ant colony techniques to minimize the fuel consumption and emission levels. It uses the route construction to build routes and assign them to vehicles, it also applies pheromone deposition and pheromone evaporation to update the route link costs. These ant colony techniques are customized to be suitable for transportation networks. In the case of normal operation, the ACO-ECO performance is similar to the SPF-ECO. While for link blocking scenarios, the ACO-ECO reduces the fuel consumption, average trip time, stopped delay, and most of the emission levels. An important advantage of the ACO-ECO is its flexibility; where its parameters (error factor, maximum updating time, maximum updating distance, and evaporation interval) can be tuned in order to achieve better performance. The fine tuning and testing of these parameters are an important future extension of the work presented in this paper.

Another future research is to study the effect of each of the new updating methods on the network traffic and studying the trade-off between the reduction in the fuel consumption and emission levels and the communication network traffic load. The market penetration rate is an effective and important parameter that should be studied. Also, it is important to study the effect of the communication network on the ACO-ECO performance.

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