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Route planning model of multi-agent system for a supply chain management

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ABSTRACT

Sometimes in travel planning, finding the best route to the road transportation network by considering the environmental conditions that are affecting the actual time travel of the travellers are vital especially in handling the logistic operations in supply chain management (SCM). Furthermore, the policy strategy is needed in order to influence the managers or drivers to find the optimum and the most effective route for a trip plan in supporting the logistic operations of SCM. In this paper we analyze the effectiveness of the coordination model of the environmental conditions that are affecting for the travelling time based on multi-agent system for a road transportation network for supply chain management. A number of experimental cases have been used to evaluate the proposed approach transportation network problems in some Malaysian cities. Finally, experimental results affirmed that the proposed approach is practical and efficient.

1. Introduction

In the route guidance for supply chain management (SCM) process, route planning should take the travelers' responses to the guidance strategy into account. Guidance control decision making of route planning will affect the traveler's route choice behaviors. On the other hand, the travelers' route choices will determine the network condition in turn will reflect on the guidance control decision making of route planning (Binjin, Keping, Mingjun, & Heng, 2007; Dexin, Zhaosheng, Yuan, & Jianping, 2006). Reduction of vehicle delays could be achieved by studying the transportation environment conditions (Tu, 2008; Zegeye, 2010), such as weather, traffic information, safety of road (Eurlings, 2011), incident and accident, seasonal effects (time-of-day, day-of-week and month) and cultural factors, population characteristics, traffic management and traffic mix by giving a priority trip plan to vehicles (Fig. 1). Fig. 1 shows the factors that influence travel time distribution. Therefore, prediction of travel time needs to be done using the available road environment data along with logical assumptions. For example, it can be assumed that travel demand at a certain time interval during the day is constant during weekdays (Zegeye, 2010). So far, different techniques for the mitigation of congestion have been forwarded. One of them is to improve and expand the public transport system (Jamie Houghton & Colin, 2009). According to the traffic flow theory, travel time is the total time required for a vehicle to travel from one substantial point to another over a specified route under prevailing conditions such as work zone, weather and road conditions (Mahmoud, 2009). Congestion leads to a decrease in accessibility, travel time loss and air pollution (Smith, Holt, & Park, 2004). So far, different techniques for the mitigation of congestion have been forwarded. One of them is to improve and expand the public definition of travel time as the time it takes travelers to traverse a particular corridor. (Smith et al., 2004) defines travel time as the amount of time required to travel from one point to another on a given route. (Van Lint, 2004) defines the individual travel time on a route "*r*" at departure time "*t*" as the time it takes an individual traveler to traverse that particular route. According to the traffic flow theory, travel time is the total time required for a vehicle to travel from one substantial point to another over a specified route under prevailing conditions such as work zone, weather and road conditions (Mahmoud, 2009). In these researches, route planning was generally considered the unique decision maker that determined the optimal state of the dynamic system and it depended on the travelers' behavior (Shi, Na, & Chun-bin, 2008) and according to the manager's willingness completely (An, Na, & Chun-bin Hu, 2008). These assumptions were too ideal and did not take into account the traveler's responses to the strategy and the influence of these responses on the manager's strategy making their studies critically defective. Recently, multi-agent negotiation is one of the most effective methods in solving dynamic route choice problems (Adler, Satapathy, Manikonda, Bowles, & Blue, 2005; Paul, Lawrence, Linda, Johanna, & Fredrik, 2005). It is obvious that physical as-sociability of a traffic network has provided convenience for selective negotiation and communication among agents, and it simplifies information transmission greatly. Furthermore, this multi-agent system is more suitable for solving the corresponding problems of complex systems, such as modeling and solving, for it can generate routes quickly to meet the real-time requirement of a system (An et al., 2008).

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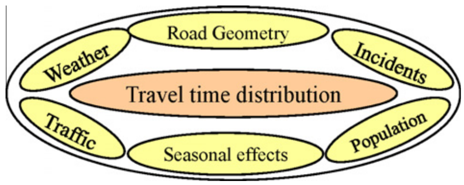


Fig. 1. Factors influencing on the trip times distribution.

This paper consists of five main sections. Section 2 describes the meaning of route planning and outlines related work. This is followed by a description of the characteristics of the SCM, route transportation network (RTN) and structure of route planning for SCM in Section 3. The proposed route planning model and algorithm are provided for SCM in Section 4. Sections 5 and 6 are devoted to using of the route planning in a case study and simulation results. Section 7 provides conclusions and suggestions for future research.

2. Related works

A case study of an agent-based modeling application to the optimization and management of a corrugated-box manufacturing plant was studied by Belecheanu, Luck, and Darley (2005), Kovalchuk (2009). A set of agents was defined for the specific performance of a function with a set of inputs in Kovalchuk (2009), Uppin (2010). In this work, each agent manages a specific function of a supply chain management (SCM) and share information with the other agents. Agents communicate with other agents based on the local road transportation network information. An agent presents sufficient knowledge to make obligations for users in a mode that would be intelligent (Uppin, 2010). The multi-agent system is one of the most effective methods in solving dynamic route choice problems (Shi et al., 2008). However, the overall characteristics of an agent are autonomy, intelligence, learning, interaction, communication, cooperation, goal orientation, reactivity and mobility (Uppin, 2010).

3. Route planning model for SCM

Some critical factors in SCM are considered and measured for travelling across a road transport network: energy use, time, waste (for products), traffic safety and health (for goods and humans), accessibility and economic wealth.

The objectives of this system are:

Maximize security	Maximize the safety of products and goods
Maximize usage of transportation tools	Minimize operating costs
Minimize air pollution	Minimize travel cost
Minimize vehicle usage	Minimize trip time
Minimize ecosystem impacts	Maximize productivity
Minimize energy consumption	Maximize reliability
Maximize safety of the driver and other people	

The new classification system covers all public roads and extends to the presently unclassified rural and urban roads. The main thrust of the approach is to make the classification more objective and consistent by specifying quantifiable parameters (traffic, population, and spacing) to guide the selection of the appropriate road classes. It is also a dynamic system where road classes can be periodically reviewed to adapt to changes in traffic, function etc.

3.1. Road safety and security

The Road Safety Council is a registered society under the Registrar of Societies, Malaysia. At present, it has a strong membership of 47, comprising 30 government agencies and 17 nongovernmental agencies. The patron of the council is the prime minister. He also chairs the high-level cabinet committee on road safety. The transport minister chairs the Road Safety Council with his deputy as the deputy chair. The Undersecretary of the Land Transport Division is the secretary-general of the council, and the treasurer comes from one of its 47 members. The council has a secretariat based at the Land Transport Division, with four full time staff members. It holds an executive committee meeting comprising 15 members (12 members are appointed by the transport minister and three are from the Ministry of Transport (MOT)). The members of the executive council are representatives from the Attorney General's Office, Kuala Lumpur City Hall, Malaysia Highway Authority, Ministry of Education (MOE), Ministry of Housing and Local Government (MHLG), Ministry of Information (MOI), Ministry of Works (MOW), The Royal Malaysian Police (PDRM), Public Works Department (PWD), Road Transport Department (RTD), and the Universiti Putra Malaysia (UPM). The council meets about four times a year and is chaired by the secretary general of the MOT, with the deputy secretary general (planning) as the deputy chair. The council meets once a year (during its annual general meeting) to review the road safety situation in each member state as well as to obtain feedback from these states. The member states also report their activities for the year that ended. The council's main activity is to promote road safety in the country. The main source of funds comes from an MOT grant. The main activities involve organizing and launching safety campaigns, educational talks, and road safety exhibitions. The bulk of the funds are for multimedia campaigns on road safety. These high-level campaigns are targeted toward pedestrians and motorcycle, and automobile drivers. The campaigns are conducted for a period of two years through television, radio, billboards, newspapers, magazines and school posters. Two major multimedia campaigns, which were organized recently, were the Motorcycle Safety Campaign (I) (1997–2000) and Motorcycle Safety Campaign (II) and Pedestrian Safety Campaign (2001–2002). The council also allocates some funds for road safety research, which is carried out by the Road Safety Research Centre, based at Universiti Putra Malaysia. In addition, the council allocates a portion of the grant to all member states to carry out road safety activities, such as workshops, seminars, talks, campaigns, competitions, quizzes and exhibitions.

Factors that are relevant for road engineering may include those where a road defect directly triggers a crash, where some element of the road environment misleads a road user and thereby creates an error, or where some feasible physical alteration in the road would have made the crash less likely. Data relevant to road safety (Eurlings, 2011) are collected from a number of different sources, including police reports and hospital admissions. This data can then be coded and entered into a computerized database system. In terms of route planning and the design and maintenance of road network, the following four elements that affect road safety have been identified:

- Safety-awareness in the planning of new road networks,
- The incorporation of safety features in the design of new roads,
- Safety improvements to existing roads, and
- Remedial action at high-risk crash sites.

The safety requirement for intersections can be defined as an interval with a desired level to be satisfied and a definite level that must be satisfied. If the expected number of accidents does not exceed the desired level, a priority intersection should be selected. If it exceeds the definite level, a control intersection should be selected. If the number is between the defined levels, a control intersection should be considered. The selection can be made using diagrams with the relation between the safety levels and the traffic volumes on the primary and secondary roads. For example, the following diagram is for a 3-leg intersection (T-intersection) with 70 km/h speed limit on the main road based on Swedish accident statistics.

3.2. Traffic conditions

Both the safety level and the capacity of different intersection types depend on the speed limit on the primary road. The speed limit for the main road must thus be decided. The requirements for speed can be based on road classification and location.

3.3. Road geometry and regulation

The classification of the type of road depends on the physical condition of the roads in a route. A road in good condition enables the vehicles to minimize trip time. Conversely, a bad road may increase trip time and, in sequence, increase operational cost. Unlike the previous two parameters, the type of road parameter consists only of three membership functions with the same data range. This parameter is set to have three parameters in order to be easy to differentiate the good condition from the bad condition of the road. A road is feasible for the public vehicle when the type of road is ranging over Average to Good. Table 1 shows the three types of roads-Good, Average and Bad and their defining conditions.

3.4. Traffic Management Architecture

Traffic Management Architecture (TMA) is a structured description of the complex system of traffic and traffic management measures. It can be used to develop and implement a consistent and accepted route planning strategy in terms of policy objectives, set of traffic management measures and the necessary technical and information infrastructure. The TMA consists of five sub-architectures, each describing one aspect of traffic management. For defining and using a consistent set of traffic management measures the Traffic Control Architecture is used. For the integration of the hardware and software, an Application Architecture is defined. The Architecture of the Technical Infrastructure describes the general ICT services in traffic management systems. The Information Architecture should harmonize the exchange and use of information and finally, the organization architecture gives a picture of the organization required to facilitate traffic management. Of these five sub-architectures the Traffic Control Architecture is the most developed one and plays a leading role in the design, implementation and operational use of traffic management.

3.5. Speed limits

There may be various reasons associated with the causes of road accidents, and they may be categorized into two main groups, transport demand and unsafe operation. Adverse weather phenomena undermine the qualities of all aspects of road transportation and increase the risk of road accidents and casualties. The main objective of this report is to gather information on weather-related accident issues and to reveal risks caused by adverse weather conditions even though it is not as serious as snow-related problems. The speed of motor vehicles is at the core of the road-traffic injury problem. Speed influences both road traffic injuries and arrival time consequences. Crash risk increases as speed increases, especially at road junctions and while overtaking as road users underestimate the speed and overestimate the distance of an approaching vehicle. The speed limits in Malaysia are 110 km/h on Motorways, 80 km/h outside of built-up areas and expressways and 50 km/h within towns. A number of factors influence the speed choice of drivers.

1. Driver-related factors (age, sex, alcohol level and number of people in the vehicle),
2. Factors relating to the road and the vehicle (road layout, surface quality, vehicle power, and maximum speed), and
3. Traffic-related and environment-related factors (traffic density and composition).

3.6. Vehicle condition

Vehicle-condition rating system is classified in Table 2. Vehicle condition can be specified as follows:

1. **Excellent:** A close to perfect original or a very well restored vehicle. Generally, well-done body-on restoration that has been fully detailed may qualify. Everything works as new. The vehicle is stunning to look at and any flaws are trivial and not readily apparent.
2. **Very Good:** An extremely presentable vehicle showing minimal wear or a well-restored vehicle. It needs no mechanical or cosmetic work. Runs and drives smooth and tight. All areas have been fully detailed.
3. **Good:** Presentable inside and out with some signs of wear. Not detailed but very clean. The body should be straight and solid with no apparent rust and absolutely no rust-through anywhere. Shiny, attractive paint but may have evidence of minor fading or checking or other imperfections. Runs and drives well. It may need some minor mechanical or cosmetic work but is fully usable and enjoyable.
4. **Fair:** Runs and drives fine but needs work throughout the vehicle. Body shows signs of wear or previous restoration work. Any rust should be minimal and not in any structural areas. Cosmetics, body and mechanics all need work to some degree.

Table 1
Type of road.

Linguistic value	Condition
Good	Normal traffic, separated tracks for different models of vehicles.
Average	Different models of vehicles in the same track. None motorized vehicles; hilly road is less than 5 km.
Bad	Bad congested, too many pedestrians, hilly road is more than 5 km.

Table 2
Vehicle condition rating system (Source: Laver, Schneck, Skorupski, Brady, Cham, & Hamilton, 2007).

Rating	Condition	Description
1	Excellent	No visible defects, near new condition
2	Very Good	Some (slightly) defective or deteriorated component(s)
3	Good	Moderately defective or deteriorated component(s)
4	Fair	Defective or deteriorated(s) in need replacement
5	Poor	Critically damaged component(s) or in need of immediate repair

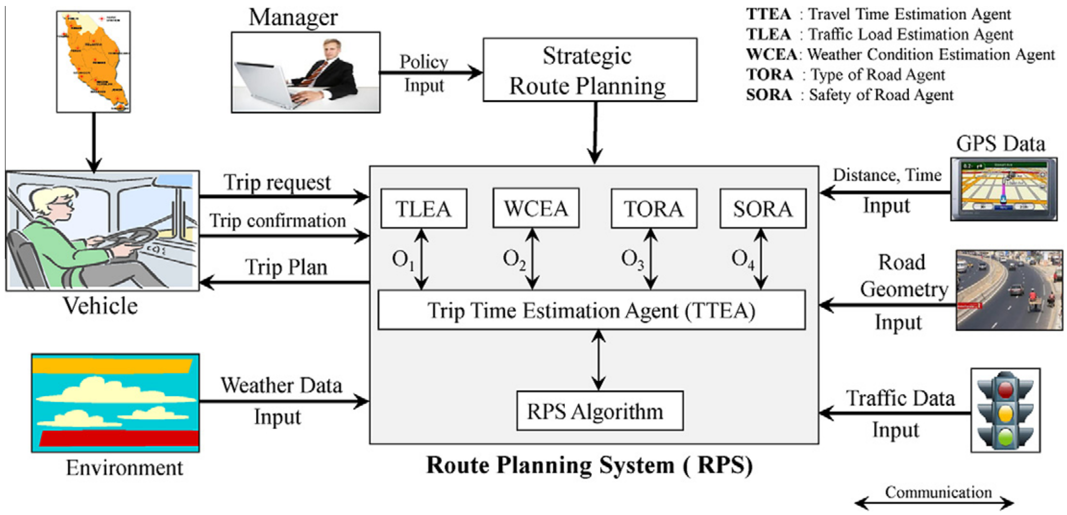


Fig. 2. The use of integrated agents to support route planning.

5. **Poor:** In need of complete restoration, but is complete and not a rust bucket beyond repair. It may or may not run and drive.

4. MAS proposed for supply chain management

In this study, two types of agents were applied to respond to various types of SCM services in the RPS, namely, control agent and estimate agent. As mentioned previously, agents negotiate and communicate with the other agents, perform the operations based on the local available information, and may pursue their local goals. If the software agent is suitably modeled, RPS can improve the speed and quality of work in SCM and transportation network activities (Srinivasan, Kumar, & Jaglan, 2010). We have identified some agents in the RPS to utilize a subset of managing and controlling elements of the supply chain management. The controlling SCM elements help in decision making by utilizing various agents for demand, supply for a supply chain management (Kovalchuk, 2009) and transportation control within the routing path. In the SCM, some critical and real-world factors are considered and measured, such as energy use, weather, time, safety, road traffic, accessibility and economic wealth. Each of the factors can be reported by an agent system, which can be defined as the following:

$$Ag = \{Ag_1, Ag_2, Ag_3, \ldots, Ag_n\} \text{ s.t. } \quad n \in \mathbb{N}$$

We have used four agents Ag1, Ag2, Ag3, Ag4 and Ag5 named as TLEA, WCEA, TORA, SORA and TTEA (Trip Time Estimation Agent), respectively. The objectives of this system are to maximize the use of transportation tools, ensure the safety of the driver and other people, improve productivity and reliability, as well as minimize air pollution, energy consumption, operating costs, travel cost and trip time. Fig. 2 shows the use of integrated agent to support the RPS. These agents' details with a related input and output of this study are outlined below:

4.1. Traffic Load Estimation Agent (TLEA)

This agent uses the current traffic data of routes to estimate and evaluate the traffic status of each route as vehicles pass through and estimate the suitable rate of route traffic during the trip across the route. TLEA is working in real time, and it will update the traffic status of each route in RTN. This traffic load estimation can be computed by using the present data and also by considering the historical information on each route. The result of this estimation will be used by Trip Time Estimation Agent (TTEA) of RPS.

4.2. Weather Condition Estimation Agent (WCEA)

Weather Condition Estimation Agent (WCEA) predicts the weather based on data from a local weather station or the Internet. The results obtained by this agent will be used by the TTEA agent for the RPS.

4.3. Type of Road Agent (TORA)

This agent reports the type of road that will be avoided when there are alternative links that have a better type. TORA should supervise this status and deliver its result to TTEA for consideration in the best route suggestion algorithm.

4.4. Safety of Road Agent (SORA)

This agent reports and evaluates the safety rate of each route with regards of the historical data saved in the system and also specific input data, including weather data, current status of route traffic density and so on. The output of this agent is the computed rate of routes safety that will be used by the DRP algorithm (DRPA) for route planning in TTEA (Travel Time Estimation Agent).

4.5. Trip Time Estimation Agent (TTEA)

Trip Time Estimation Agent (TTEA) evaluates the route distance and vehicle speed in each route by using the road-network map data saved in the system and specific input data including time, route distance and so on. TTEA can be elaborated from the TLEA data or from direct measurements of trip times. The output of the agent is calculated using the RPA algorithm for finding route priority in the TTEA. This agent is the decision-making brain of the proposed model. The roles of the agents are to receive cost-effective information from the environment agents (TLEA, WCEA, TORA and SORA) and calculate the real route rate based on the other agent's information and the route planning system algorithm (RPSA) result. The RPSA uses the information of the agents (TLEA, WCEA, TORA and SORA). The origin and destination of vehicle data, such as time and distance of route, the fuel consumption of the vehicle and other required data will be entered to enable this agent to assess the best route from the manufacturer site to all

Table 3
The rates of integrated agent outputs of each route (average speed: 90 km/h).

Route	Dist. (km)	AvgSpd (km/h)	TrpTim (m)	O_{TLEA}	O_{WCEA}	O_{TORA}	O_{SORA}	ActTim (m)
KB ↔ IP	343	61	337	0.10	0.00	0.10	0.05	450
KB ↔ GM	189	63	181	0.10	0.00	0.05	0.00	213
KB ↔ JB	787	75	626	0.05	0.00	0.05	0.05	736
KB ↔ KN	365	60	365	0.15	0.10	0.05	0.05	561
KB ↔ ML	593	68	520	0.15	0.05	0.05	0.05	742
KB ↔ KT	169	66	153	0.05	0.00	0.05	0.10	191
KB ↔ KL	461	66	417	0.05	0.05	0.05	0.05	522
GM ↔ IP	165	61	162	0.10	0.05	0.00	0.05	202
GM ↔ KL	267	67	238	0.10	0.05	0.05	0.00	297
GM ↔ ML	406	72	338	0.05	0.00	0.00	0.00	356
GM ↔ JB	596	80	445	0.05	0.05	0.05	0.05	556
GM ↔ KN	342	71	290	0.05	0.10	0.05	0.00	362
GM ↔ KT	286	63	273	0.10	0.10	0.04	0.01	365
KT ↔ KL	435	72	364	0.00	0.00	0.00	0.05	383
KT ↔ KN	199	55	215	0.05	0.05	0.05	0.15	308
KT ↔ IP	444	65	408	0.00	0.05	0.15	0.05	544
IP ↔ ML	346	93	224	0.10	0.10	0.12	0.16	431
IP ↔ JB	541	95	342	0.05	0.05	0.10	0.00	427
IP ↔ KN	405	82	296	0.10	0.10	0.05	0.05	423
IP ↔ KL	202	91	134	0.05	0.05	0.10	0.10	191
IP ↔ KG	217	89	146	0.06	0.05	0.05	0.05	185
KN ↔ KG	268	78	205	0.06	0.05	0.05	0.00	245
KN ↔ JB	360	75	289	0.05	0.15	0.03	0.02	385
KN ↔ ML	255	69	221	0.10	0.10	0.05	0.05	316
KN ↔ KL	253	86	177	0.05	0.15	0.00	0.00	222
KL ↔ KG	38	62	037	0.15	0.00	0.05	0.00	46
KL ↔ KG	25	56	027	0.10	0.05	0.00	0.00	32
KG ↔ KJ	50	60	050	0.15	0.00	0.00	0.00	59
KG ↔ ML	166	79	126	0.07	0.05	0.00	0.00	143
KG ↔ JB	356	90	238	0.06	0.05	0.05	0.00	283
KJ ↔ ML	124	75	099	0.05	0.04	0.04	0.01	115
KJ ↔ JB	314	89	212	0.05	0.00	0.00	0.05	235
KL ↔ ML	136	85	096	0.11	0.05	0.10	0.05	139
KL ↔ JB	274	88	186	0.10	0.05	0.10	0.05	266
ML ↔ JB	211	91	139	0.05	0.00	0.00	0.00	146

Note: Dist. is the distance in kilometres (km) between the Malaysian cities based on Google Maps data from the Internet.
AvgSpd is the average speed of vehicle (per km/h) in this travel.
TrpTim is the route Trip-time (in minutes) computed based on average speed of the vehicle (AvgSpd) and travel distance (Dist.).
O_{TLE}A, O_{WCEA}, O_{TORA} and O_{SORA} are the outputs of TLEA (Traffic Load Estimation Agent), WCEA (Weather Condition Estimation Agent), TORA (Type of Road Agent), SORA (Safety of Road Agent) and TTEA (Trip Time Estimation Agent) respectively.
ActTim is the actual trip time (in minutes) computed by using Eq. (3).

Table 4
The actual time of JB–KL at different times within a day.

Trip time hh:mm	AvgSpd (km1 h)	Distance (km)	TrpTim (m)	O_{TLEA}	O_{WCEA}	O_{TORA}	O_{SORA}	$f(t)$
04:00				0.00	0.00	0.02	0.00	191
06:00				0.04	0.00	0.03	0.00	201
08:00				0.02	0.00	0.02	0.00	195
10:00				0.05	0.00	0.01	0.00	199
12:00				0.10	0.00	0.00	0.00	208
14:00	88	274	186	0.05	0.00	0.00	0.00	197
16:00				0.08	0.00	0.00	0.00	203
18:00				0.10	0.00	0.00	0.00	208
20:00				0.10	0.00	0.00	0.00	208
22:00				0.08	0.00	0.00	0.00	203
24:00				0.06	0.00	0.00	0.00	199

Noted: O_{TLEA}, O_{WCEA}, O_{TORA}, O_{SORA} and O_{TTEA} are the outputs of TLEA, WCEA, TORA, SORA and TTEA, respectively.
$T_{JB\text{-}\rightarrow KL}$ is the route Trip-time (in minutes) received from Google Maps.
$f_r(t)$ is the actual trip time computed by using Eq. (3).

customers. These agent decisions can be based on the RPSA. Additional information such as the weather forecast data are also considered. However, according to the definition of TTEA, O_{TTEA} and the other agent output, as mentioned earlier, we can define the equations as follows:

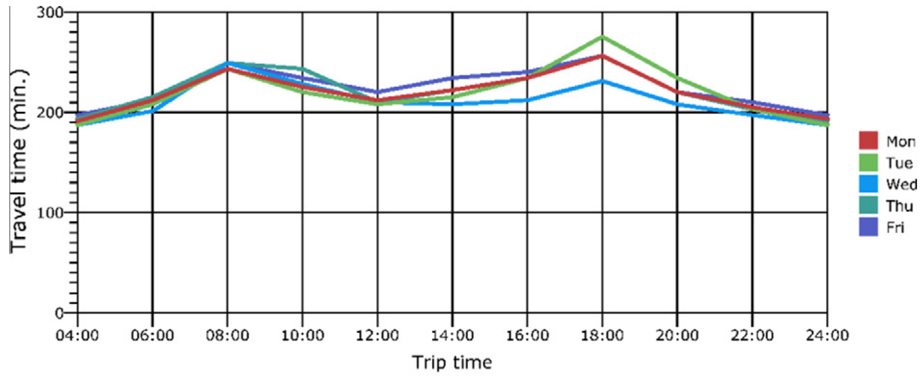
Summation of factors =

$$\sum_{i=1}^{n}\overline{O}_i \quad \text{s.t.} \quad \bar{o}_i \in [0,1]; \quad i \quad \text{and } n \in \mathbb{N} \tag{1}$$

If we limit the number of factors to four, therefore $n = 4$, the equation is:

$$\sum_{i=1}^{4}\overline{O}_i = \overline{O}_{TLEA} + \overline{O}_{WCEA} + \overline{O}_{TORA} + \overline{O}_{SORA} \tag{2}$$

$$\text{Subject to : ActTim}_{(m)} = 60^{*}\text{Distance}\Big/\left[\left(1-\sum_{i=1}^{4}\overline{O}_i\right)^{*}\text{AvgSpd}\right] \tag{3}$$



	04:00	06:00	08:00	10:00	12:00	14:00	16:00	18:00	20:00	22:00	24:00
Mon	191	212	243	225	212	222	234	256	220	205	193
Tue	187	208	243	220	208	215	234	275	234	203	187
Wed	187	201	249	228	210	208	212	231	208	197	187
Thu	193	215	249	243	210	222	234	256	220	203	191
Fri	197	212	249	234	220	234	240	256	220	210	197

Fig. 3. The actual trip time from JB to KL at different times within a week.

Assuming that "*r*" = *route*, $f_r(t)$ = ActTim then

$$f_r(t) = 60 * \text{Distance}/\left[\left(1 - \sum_{i=1}^{4}\overline{O}_i\right) * \text{AvgSpd}\right] \quad (4)$$

To demonstrate the model described earlier, let us take the following two examples as case studies.

Example 1: The actual time at 11:30 h in the route of Johor Bahru (JB) → Kuala-Lumpur (KL) can be as follows:

$$\begin{aligned} f_{JB\to KL}(11:30) &= 60 * \text{Distance}_{JB\to KL}/\left[\left(1 - \sum_{i=1}^{4}\overline{O}_{JB\to KL}\right) * \text{AvgSpd}(11:30)\right] \\ &= 60\,\text{minutes} * 274\,\text{km}/[(1-0.10) * 88\,\text{km/h}] \\ &= 208\,\text{minutes} \end{aligned}$$

Example 2: Regarding Eqs .(3) and (5), the actual time of JB → KL at different times within a day can be calculated (see Table 4) as follows:

Fig. 3 and Table 5 show the actual trip time from *JB* to *KL* at different times within a day. Although, the starting time is 04:00 h, the real traveling time is 187 min, while the same distance takes 249 min when the starting time is 08:00 h. The trip time variation ($\Delta(x_t)$) noted is due to the road traffic and weather condition (Table 4). Between 08:00 h and 12:00 h, there is a slight decrease in trip time. However, 12:0018:00 h signifies a little increase in trip time. Finally, the traffic trip time decreases as the day ends and enters into the following morning. However, we can define an equation at time t', $Y_t = f(x_t + \Delta(x_t))$ such that $\Delta(x_t)$ is the variation of x_t. However, the goals of TTEA are as follows:

(a) Receiving both travel origin and destination (s,d) from the vehicle (Fig. 2),
(b) Finding the primary path, $R_{(s,d)}$ (including the ideal times and distances for multiple routes), regarding the travel origin and destination,

$$R_{(s,d)} = \sum_{i=1}^{d}\sum_{j=1}^{d} R_{(s_i,d_j)} \quad \text{s.t.} \quad i\&\, j \geqslant 1;$$

(c) Adjusting the trip plan to satisfy the travel objectives of the driver,
(d) Proposing the path information using Google Maps (time and distance) to the agents TLEA, WCEA, TORA and SORA,
(e) Adapting the route guidance in response to updated weather, traffic, fuel capacity and safety advisories,
(f) Receiving the route rate and route cost (time) of each agent TLEA, WCEA, TORA and SORA,
(g) Computing the total route rate, O_{TTEA},
(h) Proposing the path information and total route rate to the RPSA (route, actual time and O_{TTEA}),
(i) Receiving the optimal path (R^*) from RPSA and saving it in the database, $R^*_{(s_1,d_1)}, R^*_{(s_2,d_2)}, \ldots, R^*_{(s_n,d_n)}$ and
(j) Reporting the most suitable trip plan to the vehicle.

$$R^*_{(s,d)} = \sum_{i=1}^{d}\sum_{j=1}^{d} R^*_{(s_i,d_j)} \quad \text{s.t.} \quad i\&\, j \geqslant 1;$$

The next subsections, the problem formulation and Route Planning Algorithm (RPA) is presented.

4.6. Route planning problem formulation and properties

A road-directed graph, presented by $\overrightarrow{G} = (V, E)$, is a directed dynamic route planning system (DRPS) based on an electronic map, a set of "*V*" nodes and "*E*" directed edges. Each $R_{(s,d)}$ edge is a non-negative number, which represents the cost, while "*s*" is a start node and "*d*" is a finish node connected to $R_{(s,d)}$. Let us consider a directed graph, *G*, which is composed of a set of "*v*" nodes and a set of "*e*" directed edges, and set a number of edges as the cost table. If $S = \{s_1, s_2, \ldots, s_n\}$, $D = \{d_1, d_2, \ldots, d_n\}$ then $R_{(s,d)} = R_{(s_2,d_2)} + \cdots + R_{(s_n,d_n)}$. $R_{(s,d)}$ consists of the sum of all edge distances (costs) in the network path. Therefore, according to the trip origin (s) node and destination (d) node, this issue can be solved as an optimization problem based on the real transportation network that can be defined as follows:

$$R_{(s,d)} = \min \sum_{i=1}^{d}\sum_{j=1}^{d} \alpha R_{(s_i,d_j)} \begin{cases} \alpha = 1 & \text{There is a link exists btwn } i \text{ and } j \\ \alpha = 0 & \text{Otherwise} \end{cases} \quad (5)$$

where:

- i and j are the current state movements into the right and bottom side directions, respectively.
- $R_{(s,d)}$. is the shortest path from an origin node, "*s*" to a last node, "*d*".
- α is a binary digit (0 or 1).
- Links are independent of each other.

Table 5
Traffic rate policy based on agents' output in Case 1.

Time (hh:mm)	Dist. (km)	Speed (km/h)	Day	O_{TLEA}	O_{WCEA}	O_{TORA}	O_{SORA}	$f(t)$ (m)
04:00	274	88	Sat	0.00	0.00	0.02	0.00	191
			Sun	0.00	0.00	0.01	0.00	189
			Mon	0.00	0.00	0.02	0.00	191
			Tue	0.00	0.00	0.00	0.00	187
			Wed	0.00	0.00	0.00	0.00	187
			Thu	0.00	0.00	0.03	0.00	193
			Fri	0.01	0.00	0.04	0.00	197
06:00	274	88	Sat	0.04	0.00	0.03	0.00	201
			Sun	0.03	0.00	0.02	0.00	197
			Mon	0.10	0.00	0.02	0.00	212
			Tue	0.10	0.00	0.00	0.00	208
			Wed	0.07	0.00	0.00	0.00	201
			Thu	0.10	0.00	0.03	0.00	215
			Fri	0.08	0.00	0.04	0.00	212
08:00	274	88	Sat	0.02	0.00	0.02	0.00	195
			Sun	0.02	0.00	0.03	0.00	197
			Mon	0.20	0.00	0.03	0.00	243
			Tue	0.23	0.00	0.00	0.00	243
			Wed	0.20	0.00	0.05	0.00	249
			Thu	0.20	0.00	0.05	0.00	249
			Fri	0.21	0.00	0.04	0.00	249
10:00	274	88	Sat	0.05	0.00	0.01	0.00	199
			Sun	0.05	0.00	0.03	0.00	203
			Mon	0.12	0.00	0.05	0.00	225
			Tue	0.15	0.00	0.00	0.00	220
			Wed	0.13	0.00	0.05	0.00	228
			Thu	0.15	0.00	0.08	0.00	243
			Fri	0.15	0.00	0.05	0.00	234
12:00	274	88	Sat	0.10	0.00	0.00	0.00	208
			Sun	0.12	0.00	0.05	0.00	225
			Mon	0.07	0.00	0.05	0.00	212
			Tue	0.10	0.00	0.00	0.00	208
			Wed	0.08	0.00	0.03	0.00	210
			Thu	0.06	0.00	0.05	0.00	210
			Fri	0.05	0.00	0.10	0.00	220
14:00	274	88	Sat	0.05	0.00	0.00	0.00	197
			Sun	0.06	0.00	0.07	0.00	215
			Mon	0.08	0.00	0.08	0.00	222
			Tue	0.11	0.00	0.02	0.00	215
			Wed	0.10	0.00	0.00	0.00	208
			Thu	0.10	0.00	0.06	0.00	222
			Fri	0.10	0.00	0.10	0.00	234
16:00	274	88	Sat	0.08	0.00	0.00	0.00	203
			Sun	0.08	0.00	0.05	0.00	215
			Mon	0.10	0.00	0.10	0.00	234
			Tue	0.15	0.00	0.05	0.00	234
			Wed	0.12	0.00	0.00	0.00	212
			Thu	0.13	0.00	0.07	0.00	234
			Fri	0.14	0.00	0.08	0.00	240
18:00	274	88	Sat	0.10	0.00	0.00	0.00	208
			Sun	0.11	0.00	0.03	0.00	217
			Mon	0.20	0.00	0.07	0.00	256
			Tue	0.22	0.00	0.10	0.00	275
			Wed	0.19	0.00	0.00	0.00	231
			Thu	0.20	0.00	0.07	0.00	256
			Fri	0.20	0.00	0.07	0.00	256
20:00	274	88	Sat	0.10	0.00	0.00	0.00	208
			Sun	0.16	0.00	0.03	0.00	231
			Mon	0.10	0.00	0.05	0.00	220
			Tue	0.12	0.00	0.08	0.00	234
			Wed	0.10	0.00	0.00	0.00	208
			Thu	0.10	0.00	0.05	0.00	220
			Fri	0.10	0.00	0.05	0.00	220
22:00	274	88	Sat	0.08	0.00	0.00	0.00	203
			Sun	0.12	0.00	0.01	0.00	215
			Mon	0.05	0.00	0.04	0.00	205
			Tue	0.03	0.00	0.05	0.00	203
			Wed	0.05	0.00	0.00	0.00	197
			Thu	0.05	0.00	0.03	0.00	203
			Fri	0.08	0.00	0.03	0.00	210
24:00	274	88	Sat	0.05	0.00	0.00	0.00	197
			Sun	0.05	0.00	0.01	0.00	199
			Mon	0.00	0.00	0.03	0.00	193
			Tue	0.00	0.00	0.00	0.00	187

(continued on next page)

Table 5 (*continued*)

Time (hh:mm)	Dist. (km)	Speed (km/h)	Day	O_{TLEA}	O_{WCEA}	O_{TORA}	O_{SORA}	$f(t)$ (m)
			Wed	0.00	0.00	0.00	0.00	187
			Thu	0.00	0.00	0.02	0.00	191
			Fri	0.02	0.00	0.03	0.00	197

However, real-time information systems can be acquired using installed agents, video cameras, global positioning system (GPS) and other devices on transportation routes. In this study, the travel cost (time and distance) was determined using Google Maps.

Algorithm 1: RPA

INPUT:
$G(V,E)$ be a directed graph with a set of V nodes and set of E directed edges.
PARAMETERS:
$R_{(s,d)}$, a nonnegative number stands for the cost where "*o*" start node and "*d*" is last node.
i, *j*, *k*; loop index, $G(1,i)$ is array of vertexes source; $G(2,i)$ is array of vertexes destination.
$G(3,i)$ is array of edge distance(or cost); CostArray(i) is arrayed of node costs(node weights) table
for each node and SP(i) is arrayed of the shortest path from the origin to final node.
OUPUT:
CostArray(k) is a cost data table for all nodes. SP(k), a shortest path data table for a graph.
INITIALIZATION:
// All nodes from last to first nodes are examined for the route's connected nodes.
// For each edge do the operation in two steps as follows:
set CostArray[1... node-1] = 999, CostArray(node) = 0, SP(i) = 0;
BEGIN
for all nodes
 for j = first to last edges // j is set to the destination node of edges.
  if ($G(2,j) = i$) // k is set to the source node of edges.
   cost = CostArray(i) + $G(3,j)$;
  end if
 end for
end for
for i = first to last edges
 while (the origin (k) is the same in graph, G)
  if ($G(3,i)$ = CostArray(k) − CostArray(j))
   SP(k) = $G(2,i)$;
  else
   $i = i + 1$;
   $k = G(1,i)$;
  end if
 end while
end for
END

4.7. RPA

The RPA (Algorithm 1) was computed based on TTEA information, as shown in Fig. 2. The input of this algorithm consisted of all calculated route weights based on agent data generated for each route from the origin and destination paths. The proposed algorithm is expressed based on node and route weights according to the reported agent data of each route. In this study, a "*Node weight*" is defined as the shortest distance from each node to the last network node. If "*n*" is the last node number, then "*n*−1" and "*k*" are the two node numbers connected to Node "*n*" in the network. Furthermore, regarding the node weight definition, the RPA procedure is presented in Algorithm 1. Algorithm 1 comprises the following two steps:

- **Step 1**. The distance between node "*n*−1" and node "*n*" i.e., $R_{(n-1,n)}$ is equal to the weight of a node "*n*−1" i.e., W_{n-1}. Also the distance between nodes "*n*" and node "*k*", i.e., $R_{(k,n)}$ is equal to the weight of node "*k*" i.e., W_k.

  Therefore, $R_{(n-1,n)} = W_{n-1}$ and $R_{(k,n)} = W_k$.

- **Step 2**. Similarly, the procedure in Step 1 is continued to compute the weights of all the subsequent nodes until the first node weight is computed. Finally, the weights of the first node will be used as the minimum path distance between the first node to the last node in the network, the equations can be defined as follows:

$$\begin{aligned}
R_{(n-1,n)} &= W_{n-1}, & R_{(k,n)} &= W_k; \quad \text{s.t. } k,n \in \mathbb{N}\\
R_{(n-2,n-1)} &= W_{n-2}, & R_{(k-1,n-1)} &= W_{k-1};\\
R_{(n-3,n-2)} &= W_{n-3}, & R_{(k-2,n-2)} &= W_{k-2};\\
\cdots &= \cdots, & \cdots &= \cdots;\\
\cdots &= \cdots, & \cdots &= \cdots;\\
R_{(1,2)} &= W_1, & R_{(2,3)} &= W_2;
\end{aligned}$$

However, the goals of the RPS are as follows:

1. Receiving both travel origin and destination (s,d) from vehicle (Fig. 2).
2. Receiving trip plan for the vehicle (in ideal status),

$$R_{(s,d)} = \sum_{i=1}^{d}\sum_{j=1}^{d} R_{(s_i,d_j)} \text{s.t.} \quad i\&\, j \geqslant 1;$$

3. Receiving required information via the environment agents (TLEA, WCEA, TORA, SORA and TTEA) of each route (Fig. 2),
4. Calculating total route rate and real cost (time) of each route, O_{TTEA} and actual time (ActTim),
5. Calculating a suitable trip plan to the vehicle, $R^*_{(s_1,d_1)}, R^*_{(s_2,d_2)}, \ldots, R^*_{(s_n,d_n)}$ and
6. Proposing the real trip plan to the vehicle.

$$R^*_{(s,d)} = \sum_{i=1}^{d}\sum_{j=1}^{d} R^*_{(s_i,d_j)} \quad \text{s.t.} \quad i\&\, j \geqslant 1;$$

5. Experimental study

This section summarizes the experimental results obtained using MAS for SCM in each node to acquire agent information about the next path's (or routes') status (Table 3). Hence, one of the requirements of the DRPS is real and current information about trip time of the vehicles for a continuous path that can be acquired by several detectors, such as magnet sensors, video cameras, GPS, global system for mobile communication (GSM) and other network traffic sensors on the transport route (Zhang & Xu, 2005). Other information requirements are an RTN equipment hardware, software, and communication between a simulated model and a real traffic network through the definition of the structure and routing data protocol. We have applied the roles of agents in RPS using MAS for SCM as follows:

(a) Transferring the trip-plan information acquired through the sensors to the vehicle's RPS system and the trip-plan vehicle,

$$R_{(s,d)} = \sum_{i=1}^{d}\sum_{j=1}^{d} R_{(s_i,d_j)} \quad \text{s.t.} \quad i\&\, j \geqslant 1;$$

(b) Receiving the trip route requests from vehicles through the sensor,
(c) Sending the computed optimal path information via sensor to other agents and vehicles, and

$$R^{*}_{(s,d)} = \sum_{i=1}^{d}\sum_{j=1}^{d} R^{*}_{(s_i,d_j)} \quad \text{s.t.} \quad i\&\, j \geqslant 1;$$

(d) Receiving or sending information on the route status from other collaborative agents to alert the incoming vehicles, O_{TLEA}, O_{WCEA}, O_{TORA}, O_{SORA} and O_{TTEA}.

Table 3 shows the output information of agents used in the proposed study. The parameters used in Table 3 are distance between cities, trip time (m), optimal weight of computed total route (O_{TTEA}), and actual trip time (m). The above-mentioned parameters are defined as follows:

1. O_{TLEA}, O_{WCEA}, O_{TORA}, O_{SORA} and O_{TTEA} are the outputs of TLEA (Traffic Load Estimation Agent), WCEA (Weather Condition Estimation Agent), TORA (Type of Road Agent), SORA (Safety of Road Agent) and TTEA (Trip Time Estimation Agent) respectively.
2. TrpTim is the route Trip-time calculated in minutes based on Google Maps data from the Internet.
3. ActTim is the actual Trip-time computed in minutes by using Eq. (3).
4. Distance is the distance in kilometers (km) between Malaysian cities based on Google Maps data from the Internet.

In Table 3, each agent output (O_{TLEA}, O_{WCEA}, O_{TORA} and O_{SORA}) reports a specific route weight, i.e., a number between 0 and 1, which shows the estimation status of each route, and with respect to Eqs. (1) and (3), O_{TTEA} indicates the updated route weights of each route that are computed from the results of other received agents' outputs. Therefore, using RPA to generate new route costs (actual trip time) and O_{TTEA}, the optimal path between Ipoh (IP) and Johor Bahru (JB) is changed from the path of IP → KL → JB to IP←→ JB path (Figs. 4 and 5).

5.1. Case 1

Fig. 4 shows the Malaysian roadway network graph comprising 12 routes and six cities (nodes): IP, Kuala-Lumpur (KL), Klang (KG), Kajang (KJ), Kuantan (KN), and Melaka (ML). The travel origin node is IP, and the travel destination node is ML. The distance between IP and ML (the last node) is 353 km. The figure shows that the optimal path from IP to ML in ideal route conditions (not taking into consideration many real-world factors, such as weather, road traffic, road geometry and safety), i.e., IP → KL → ML, a distance of 353 km that should take 230 min of trip time. However Fig. 5, shows the optimal path from IP to ML in real-time status and considering many real-world factors a distance of 383 km with an actual trip time of 328 min.

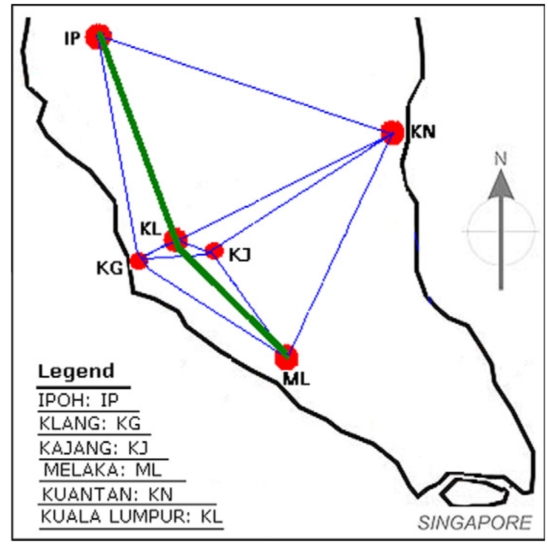


Fig. 4. The optimal path from IP to ML in ideal status in minutes (m) in Case 1.

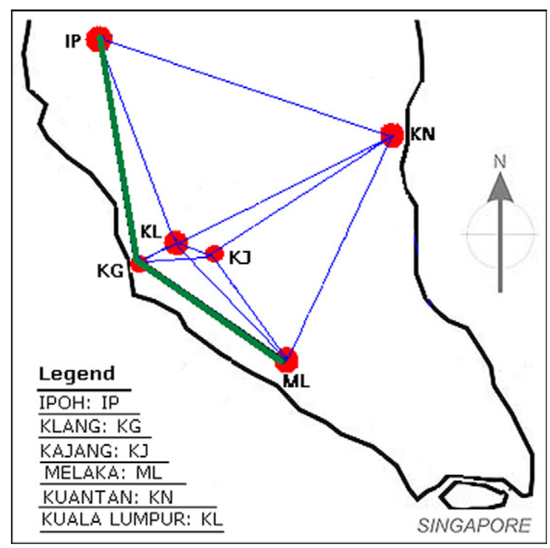


Fig. 5. The optimal path from IP to ML using MAS status in minutes (m) in Case 1.

In real-time status, SPA uses the received agent information, such as traffic agent data, weather agent data and other agent information from the installed MAS in the vehicle and roads. Therefore, by using SPA to determine the new route information of each route (actual trip time) and O_{TTEA} information, the optimal path from IP to ML is IP → KG → ML, a distance of 383 km that requires 328 min of trip time.

5.2. Case 2

Fig. 6 shows the Malaysian roadway network graph comprising 20 routes and eight cities (nodes): KG, KJ, KL, Kuala Terengganu (KT), IP, KN, ML and JB. The travel origin node is KT, and the travel destination node is JB. The distance between KT and JB (the last node) is 554 km based on Google Maps. The figure shows that the optimal path from KT to JB in ideal route conditions (not taking into consideration many real-world factors such as weather, road traffic and safety) is KT → KN → JB, a distance of 554 km that should take 504 min of trip time.

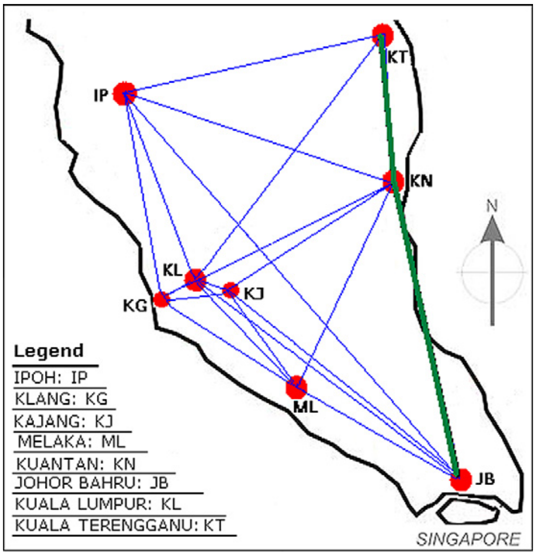


Fig. 6. The optimal path from KT to JB in ideal status in minutes (m) in Case 2.

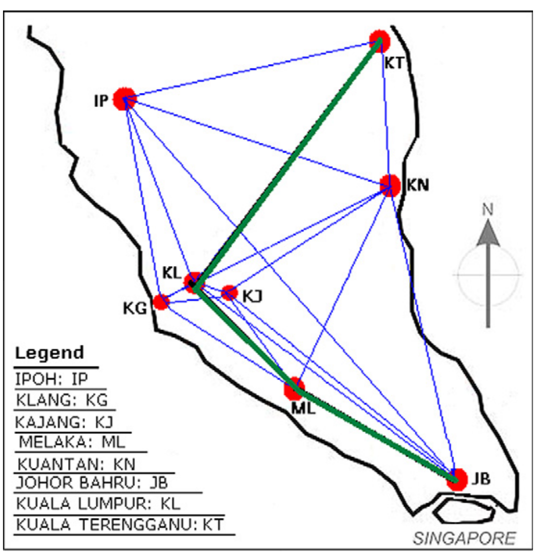


Fig. 7. The optimal path from KT to JB using MAS status in minutes (m) in Case 2.

However, Fig. 7 shows the optimal path from KT to JB in actual-time status and considering many real-world factors (such as weather, road traffic, road geometry and safety) the distance of 782 km with the actual trip time of 668 min. In real-time status, SPA uses the received agent information, such as traffic agent data, weather agent data and other agent information from the installed MAS in the vehicle and roads.

Therefore, by using SPA to determine the new route information of each route (actual trip time) and O_{TTEA} information, the optimal path from KT to JB is found to be KT → KL → ML → JB, a distance of 782 km that requires 668 min of trip time.

5.3. Case 3

Fig. 8 shows a Malaysian roadway network graph which is composed of 5 routes and four cities (nodes): KG, KJ, ML and JB. The figure shows that the optimal path from KG to JB in ideal route conditions (not considering many real-world factors such as weather, road traffic, road geometry and safety) is KG → KJ → JB,

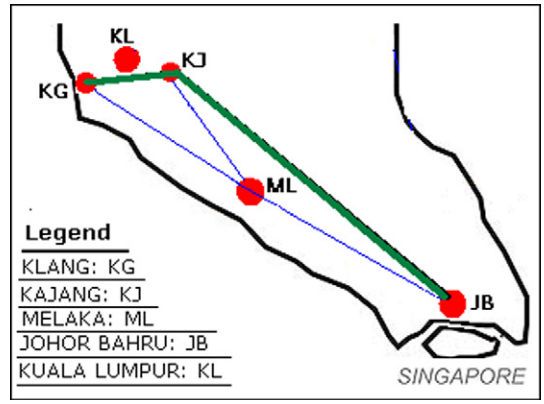


Fig. 8. The optimal path from KG to JB in ideal status in minutes (m) in Case 3.

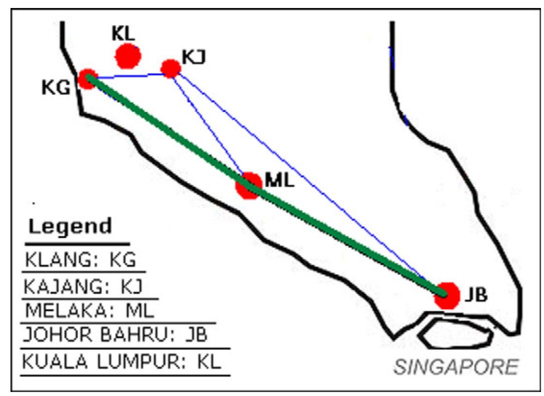


Fig. 9. The optimal path from KG to JB using MAS status in minutes (m) in Case 3.

a distance of 364 km that should take 262 min of trip time. However, Fig. 9 shows the optimal path from KG to JB in real-time status and considering many real-world factors a distance of 377 km with the actual trip time of 289 min. In real-time status, SPA uses the received agent information, such as traffic agent data, weather agent, data and other agent information from the installed MAS in the vehicle and roads. Therefore, by using SPA to determine the new route information of each route (actual trip time) and O_{TTEA} information, the optimal path from KG to JB is KG → ML → JB, a distance of 377 km that requires 289 min of trip time.

5.4. Case 4

Fig. 10 shows the Malaysian roadway network graph comprising 23 routes and nine cities (nodes): Kota Bahru (KB), KT, Gua Musang (GM), IP, KL, KG, KJ, KN and ML. The figure shows that the optimal path from KB to ML in ideal route conditions (not taking into consideration many real-world factors such as weather, road traffic, road geometry and safety) is KB → GM → KL → ML, a distance of 592 km that should take 515 min of trip time. However, Fig. 11 shows the optimal path from KB to ML in real-time status and considering many real-world factors a distance of 595 km with the actual trip time of 569 min. In real-time status, SPA uses the received agent information, such as traffic agent data, weather agent data and other agent information from the installed MAS in the vehicle and roads. Therefore, by using SPA to determine the new route information of each route (actual trip time) and O_{TTEA} information, the optimal path from KB to ML is KB → GM → ML, a distance of 595 km that requires 569 min of trip time.

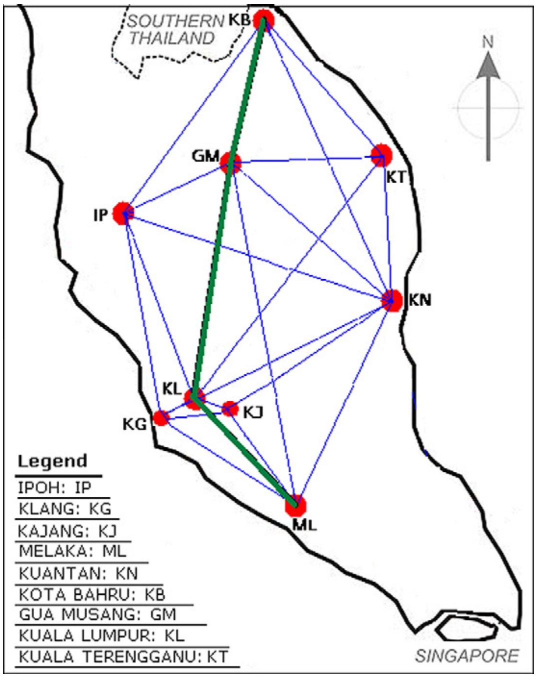


Fig. 10. The optimal path from KB to ML in ideal status in minutes (m) in Case 4.

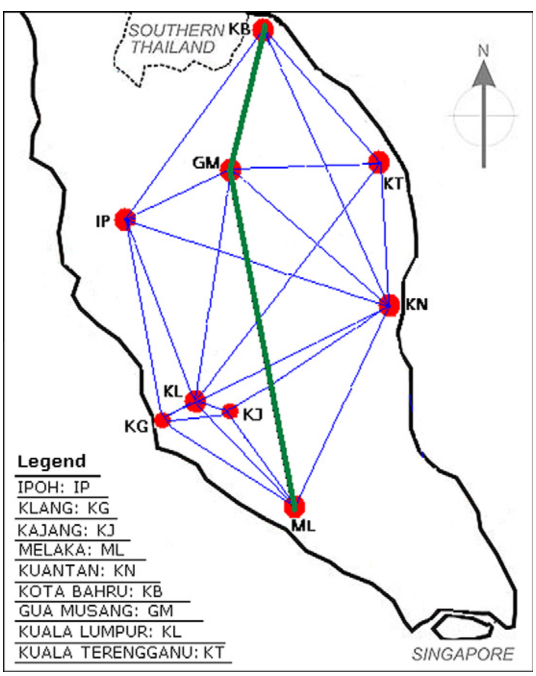


Fig. 11. Optimal path from KB to ML using MAS status in minutes (m) in Case 4.

5.5. Case 5

Fig. 12 shows the Malaysian roadway network graph comprising 15 routes and seven cities (nodes): KT, IP, KG, KJ, KL, KN and ML. The figure shows that the optimal path from KT to ML in ideal route conditions (not taking into consideration many real-world factors, such as weather, road traffic, road geometry and safety) is KT → KN → ML, a distance of 454 km that should take 436 min of trip time. However, Fig. 13 shows the optimal path from KT to ML in real-time status and considering many real-world factors a

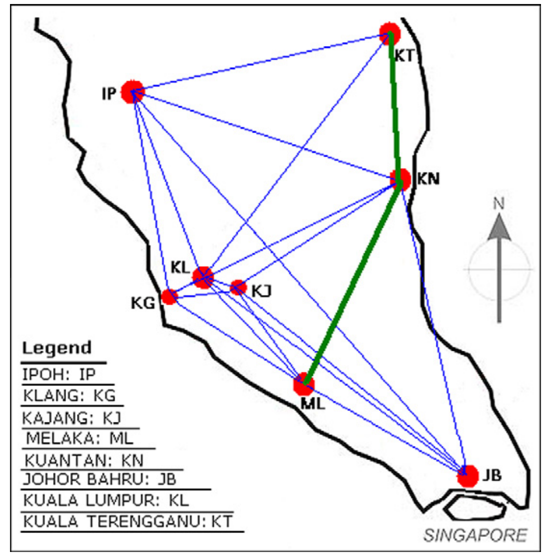


Fig. 12. The optimal path from KT to ML in ideal status in minutes (m) in Case 5.

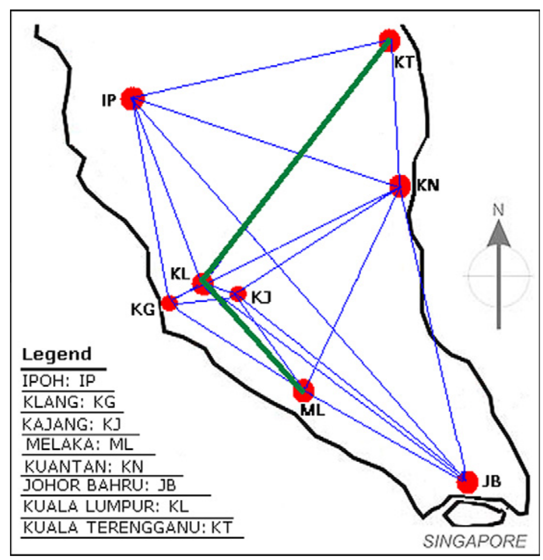


Fig. 13. The optimal path from KT to ML using MAS status in minutes (m) in Case 5.

distance of 571 km with the actual trip time of 522 min. In real-time status, SPA uses the received agent information, such as traffic agent data, weather agent data and other agent information from the installed MAS in the vehicle and roads. Therefore, by using SPA to determine the new route information of each route (actual trip time) and O_{TTEA} information, the optimal path from KT to ML is KT → KL → ML, a distance of 571 km that requires 522 min of trip time.

5.6. Case 6

Fig. 14 shows the Malaysian roadway network graph comprising 31 routes and ten cities (nodes): KB, GM, KT, IP, KL, KG, KJ, KN, ML and JB. The figure shows that the optimal path from KB to JB in ideal route conditions (not taking into consideration many real-world factors, such as weather, road traffic, road geometry and safety) is KB → GM → KL → JB, a distance of 730 km that should take 605 min of trip time. However, Fig. 15 shows the optimal path from KB to JB in real-time status and considering many real-world

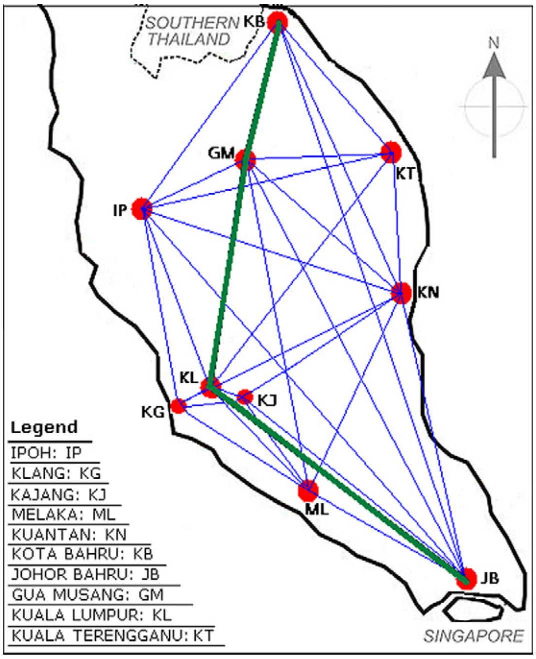


Fig. 14. The optimal path from KB to JB in ideal status in minutes (m) in Case 6.

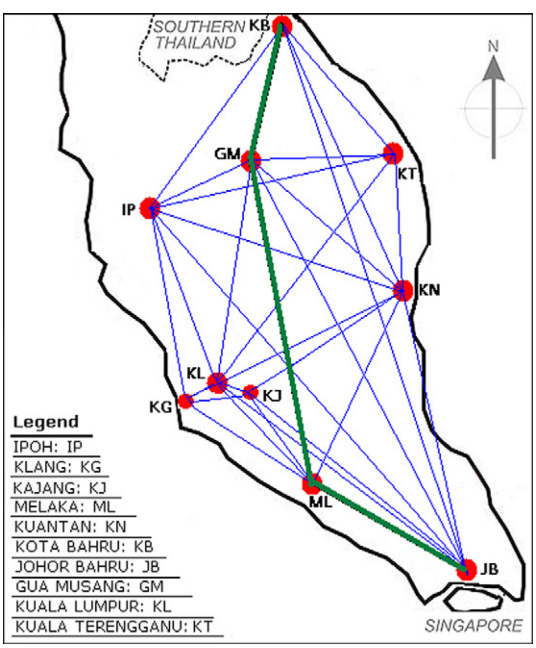


Fig. 15. The optimal path from KB to JB using MAS status in minutes (m) in Case 6.

factors a distance of 806 km with the actual trip time of 715 min. In real-time status, SPA uses the received agent information, such as traffic agent data, weather agent data and other agent information from the installed MAS in the vehicle and roads. Therefore, by using SPA to determine the new route information of each route (actual trip time) and O_{TTEA} information, the optimal path from KB to JB is KB → GM → ML → JB, a distance of 806 km that requires 715 min of trip time.

6. Simulation results and experimental comparison

In this section, simulation experiments are presented, which were carried out on different Malaysian roadway network topologies for road networks consisting of 4–10 nodes with different edges (between 5 and 31 edges). For example, the results of the new approach described in Section 4 were assessed by RPA results using several cases (Case 1 with 6 nodes and 10 routes, Case 5 with 7 nodes and 15 routes). In this section, the simulation experiments have been carried out on five different RTN topologies for a transportation network consisting of 4 to 10 nodes with different edges (5 to 31 edges). This comparison in a real transportation network shows an evaluation of the proposed RPS method using MAS. Also, with regard to Eq. (7), TimGap column reports the gap between actual times determined by using existing approach based on Google Maps data and the proposed approach (ProApproch). The TimGap equation can be defined as follows:

$$\text{TimGap} = \frac{\text{ActTim(ExistMthod)} - \text{ActTim(ProApproach)}}{\text{ActTim(ExistMthod)}} * 100 \tag{6}$$

Finally, in all the experimental cases (Table 6), the time gap performances obtained using the proposed method were less than the actual trip time generated based on Google Maps data (Fig. 16). However, this problem can be generally more accurate and its development should be studied. The suggested proposed solution will be briefly discussed in the next section.

6.1. Using MAS for SCM evaluation

This section presents the results obtained by using RPA and MAS for SCM method in the experimental case comparisons listed in Table 6.

6.2. Case 1

As depicted in Section 5.1, the RTN graph of Case 1 has 12 routes with six nodes (cities) which were used to generate a graph displaying the optimal path simulated based on Google Maps data and the proposed methods (Table 6). Comparison of the results of the proposed method and the existing approach based on Google Maps data revealed that the time gap (TimGap) is 0.61% .

6.3. Case 2

As depicted in Section 5.2, the RTN graph of Case 2 has 20 routes with eight nodes (cities), which were used to generate a graph displaying the optimal path simulated by the existing approach based on Google Maps data and the proposed methods (Table 6). Comparison of the results of the proposed method and the existing approach based on Google Maps data revealed that the time gap (TimGap) is 3.61% .

6.4. Case 3

As depicted in Section 5.3, the RTN graph of Case 3 has 5 routes with four nodes (cities) which were used to generate a graph displaying the optimal path simulated based on Google Maps and the proposed methods (Table 6). Comparison of the results of the proposed method and the existing approach based on Google Maps data revealed that the time gap (TimGap) is 1.70% .

6.5. Case 4

As depicted in Section 5.4, the RTN graph of Case 4 has 23 routes with nine nodes (cities) which were used to generate a graph displaying the optimal path simulated based on Google Maps and the proposed methods (Table 6). Comparison of the results of the

Table 6
The comparison results of the existing approach based on Google Maps data and proposed approach.

Case	Method	Optimalpath	Ref.	IdealTim (min)	ActTim (min)	TimGap (%)
Case 1	ExistMthod	IP–KL–ML	Fig. 4	230	330	0.61
	ProApproch	IP–KG–ML	Fig. 5	328	328	
Case 2	ExistMthod	KT–KN–JB	Fig. 6	504	693	3.61
	ProApproch	KT–L–JB	Fig. 7	668	668	
Case 3	ExistMthod	KG–KJ–JB	Fig. 8	262	294	1.70
	ProApproch	KG–L–JB	Fig. 9	289	289	
Case 4	ExistMthod	KB–GM–KL–ML	Fig. 10	649	515	12.32
	ProApproch	KB–M–ML	Fig. 11	569	569	
Case 5	ExistMthod	KT–KN–ML	Fig. 12	436	624	16.35
	ProApproch	KT–L–ML	Fig. 13	522	522	
Case 6	ExistMthod	KB–GM–KL–JB	Fig. 14	605	776	7.87
	ProApproch	KB–GM–MLvJB	Fig. 15	715	715	

ExistMthod is the existing method calculated based on Google Maps data from the Internet.
ProApproch is the proposed method computed by using Eqs. (1) and (3).
IdealTim is the ideal trip time computed by using Google Maps data from the Internet.
ActTim is theactual trip time computed by using the proposed method in this study.
TimGap is the calculated gap (using Eq. (7)) between actual times determined by using the existing approach based on Google Maps data and the proposed method.

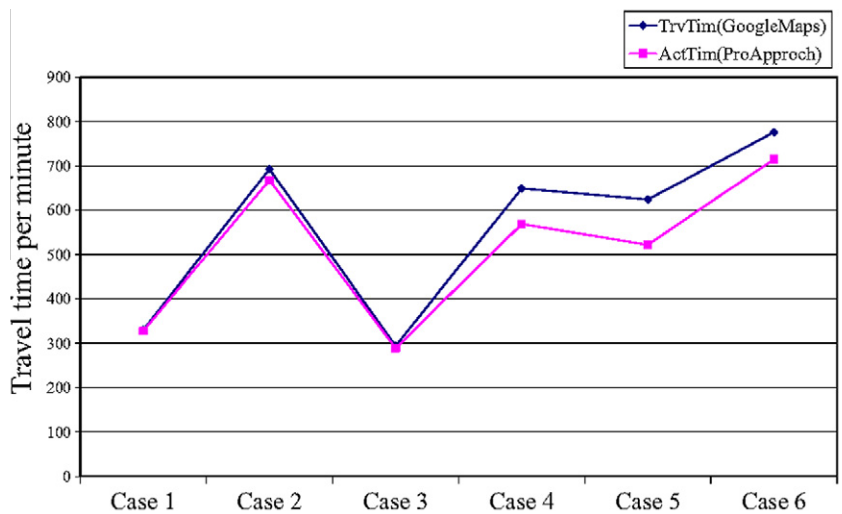


Fig. 16. Comparison between Cases 1, 2, 3, 4, 5 and 6.

proposed method and the existing approach based on Google Maps data revealed that the time gap (TimGap) is 12.32% .

6.6. Case 5

As depicted in Section 5.5, the RTN graph of Case 5 has 15 routes with seven nodes (cities) which were used to generate a graph displaying the optimal path simulated based on Google Maps and the proposed methods (Table 6). Fig. 16 shows that the time gap (TimGap) between the results of the proposed method and the existing approach based on Google Maps data is 16.35%.

6.7. Case 6

As depicted in Section 5.6, the RTN graph of Case 6 has 31 routes with ten nodes (cities) which were used to generate a graph displaying the optimal path simulated based on Google Maps and the proposed methods (Table 6). Fig. 16 shows that the time gap (TimGap) between the results of the proposed method and the existing approach based on Google Maps data is 7.87%.

However, a novel kind of RPS approach based on MAS for SCM was developed using agents installed in the entire RTN to support equipped vehicles. According to the past transportation network studies, determining the optimal and the shortest path while taking into consideration many real-world factors, such as energy use, weather, time, road traffic, accessibility, economic wealth, safety, etc., is one of the most important issues in the computer science domain. Hence, this study attempted to use the RPS using MAS for SCM to offer a new solution, including a new algorithm based on MAS and a new model for finding the optimal path in the RTN to conduct vehicles to their destination. However, to assess the MAS for SCM method, a simulation for the case study was used (Table 6), where the performances of the two methods were compared. This comparison in a real transportation network revealed the evaluation of the proposed method that is the RPS using MAS for SCM. Finally in all experimental cases, the proposed method that obtained the optimal path showed that the resulting times are less than the existing approach based on Google Maps data performance results (Fig. 16). Also, it was found that the existing approach based on Google Maps data is not real and very accurate. The trip durations of the experimental cases predicted by Google Maps data were about between 0.61 and 16.35% off from the actual trip times. Therefore, a novel kind of RPS approach for SCM was developed using the proposed method installed in the entire RTN to support equipped vehicles.

7. Conclusion

This study has presented a new paradigm and has included a new RPA based on MAS for finding the optimal path to conduct the vehicles to their destination in the SCM. It has introduced a conceptual model of RPS using MAS for SCM. This study has shown that agent technology can optimize RPS for SCM by reviewing agent applications for transportation optimization and has illustrated how a MAS can optimize the performance of this network. MAS is a coupled network of software agents that interact to solve transportation problems that are beyond the knowledge of each individual problem solved. This research has demonstrated that agent technology is suitable for solving communication concerns in a distributed transportation environment. The novelty of this study is the use of MAS in RPS for SCM, which is employed by some RTN of Malaysia for offering access to transportation network data resources. MAS attempt to solve SCM problems by collaborating between the agents, resulting in suitable answers to complex transportation network problems. The method applied by different agents to solve issues can be divided into two major categories, namely, estimation agents that estimate the size of cost-effective deciding factors of the transportation environment and prediction agents that predict the optimal cost of each possibility. In this study, each agent performed a special function of the SCM and shared its knowledge with the other agents. However, given the above-mentioned results, our contributions are as follows:

1. The study presents new applications for vehicles in the routing path of SCM,
2. It has developed a novel approach to solve the RPS problems in the underlying SCM, because the agent uses the information that it has learned to help in finding the optimal path,
3. The study provides empirical grounds for the RPS using MAS for SCM that could perform well on RTN graphs, and
4. The paper has an experimental result with enough size and dimension and it includes four important issues (RPS, MAS, RTN and SCM).

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