EcoGem: A European Framework-7 Project towards Cooperative and Intelligent Optimization of Travel Planning and Energy Saving for Drivers of Fully Electric Vehicles

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In this paper, we describe a new European Framework-7 funded research project, EcoGem, and introduce a new concept of experience sharing and intelligent optimization of route planning via machine learning approaches. While Fully Electric Vehicles (FEVs) have the potential to dramatically reduce fuel consumption, air and noise pollution within urban areas, acceptability by end users remains a problem until it is demonstrated that FEVs have a low degree of energy consumption and high degree of autonomy, especially with regards to the optimization of travel planning and energy savings. EcoGem combines machine learning techniques with communication technologies to produce an advanced driver assistance system (ADAS), which has a range of novel functionalities, including: (i) automatic generation of code-based traffic indication to allow other EcoGem enabled FEVs to share the experience for every section of route (journey) travelled; (ii) automatic learning from the past and from the on-line experience sharing to intelligently optimize the route planning and energy consumption; (iii) automatic and instant update of the route planning and optimization process via on-going experience sharing by other EcoGem enabled FEVs.

Intelligent Transport

The intelligent transportation domain can be divided into three areas: autonomous vehicles, intelligent vehicles, and smart highways. Autonomous vehicles are controlled by an on-board computer that relies on sensor information allowing the vehicle to identify various environmental conditions, pedestrians, other vehicles, potential hazards and manage numerous mechanical components of the vehicle itself. Although impressive performances have been observed from autonomous vehicles it will likely be some time before they become practical and for now a more promising approach is in the development of intelligent vehicles. Smart highways or automated highway systems are predominantly based on safety and efficiency factors but similar benefits could be obtained through vehicle intelligence.

Similar to autonomous vehicles, intelligent vehicles are also equipped with computers and sensors to perceive the environment so that they may predict driver and traffic behaviour. Appropriate actions can then be initiated in the form of a warning or travel plan information. However, this information need not be limited to the confinements of a single intelligent vehicle. Through cooperation with other automobiles, information and experiences can be shared, leading to safer highways and more efficient highway systems.

Significant progress has been made with regard to bringing vehicle intelligence technologies into passenger, commercial, and ground vehicles. For example, it is now common for engine-management to be controlled through the use of a central processor to ensure smooth running and fuel efficiency. In the case of Fully Electric Vehicles (FEVs) fuel/energy efficiency is of extreme concern. Consequently, along with engine-management we also consider the part travel planning plays for energy optimisation when driving FEVs. For example, an automatic route planning system for an FEV will not only consider fastest or shortest routes but also efficiency of route and distances to nearest recharging stations. Unfortunately such problems lead to high computational complexity due to the numerous dynamic priority constraints.

Traditional travel plan units cannot take into account unexpected conditions, such as traffic accidents, lane closures or severe weather. Furthermore, past experiences from other vehicles can aid travel plan calculation if we are traversing a route never taken before. These types of variables should be considered if global optimisation of energy efficiency is to be realised. Communication between vehicles and centralised stations is therefore of paramount importance and some models now include the ability to receive wireless live traffic data and pre-stored data [1]. With the increase of wireless technologies it will soon be possible for a vehicle to exchange information as it passes from place to place.

Fleet management involves the travel planning of a fleet of vehicles [2], with limited storage space, from a central depot to a spread of different geographical locations and customers. Research in this area is spurred by the prospect of efficient routing and scheduling of fleet vehicles when applied to emergency service vehicles and delivery vans, which would substantially reduce costs for government and industries.

Recently in-vehicle camera systems are being used for driver assistance [3] because images contain important visual information and visual sensors can be used to gain real-time data to recognise the rapidly changing environment [4]. These systems can also be used to monitor driver behaviour. For instance, driver cooperation will not necessarily be compliant with a driver support system, but by learning driver behaviour the system can always be one step ahead. For example, the update of a planned route can be initiated prior to a lane change if the intent of a lane change can be predicted. A prediction system can be built based upon a learning procedure, often using statistical models [3, 5].

There is also a close link between weather recognition and the part it plays for in-vehicle intelligence. It is well known that adverse weather conditions such as rain, snow, or fog can severely affect driving performance leading to a rise in accident rates and the need for safer routing information. Procedures to recognise weather conditions are therefore important for in-vehicle intelligence systems.

Another problem of optimisation is that associated with driver distraction [6]. Drivers are becoming increasingly distracted by various devices contained in the vehicle, such as mobile phones, navigators, PDAs, music players and even internet access systems. In this type of scenario it is necessary to account for the element of uncertainty associated with any human action. Uncertainty on a driver's compliance should be accounted for and used when updating expected travel time information.

In all aspects of in-vehicle intelligence, an optimisation procedure is required, whether it be displaying optimal information to a user, braking, engine-management or travel planning. It is currently inappropriate to apply direct use of mathematical models of traffic control [7] into route planning calculations due to the computational complexity and time required to process the model. A promising alternative is to consider machine learning and explore various systems for learning optimal solutions from different vehicle scenarios.

In the case of travel planning with constraints of time window and energy saving optimization, the problem is NP-hard. It is common practice to use heuristic methods to search the space of all possible plans in order to find near optimal solutions. Heuristics are usually combined with artificial intelligence algorithms, including simulated annealing, tabu search and genetic algorithms in an attempt to solve the problem efficiently. However these techniques have limited ability of searching the solution space and have high computational complexity. Existing research reveals that it can be possible to solve the complexity issues by changing the topology of the search space [8]. Recent work in Monte Carlo search methods in game theory has shown that world leading results can be achieved through a trade off between exploration and exploitation of the search space [9]. This particular break through has now spurred development of similar methods for use within deterministic planning applications [10].

Genetic algorithms and evolution strategies [11-13] are another popular choice to solve the dynamic vehicle routing problem but ultimately evaluation functions remain fixed, so research is more inclined towards solving these problems using machine learning techniques [3, 14]. These methods can take historical data and learn from previous driving experience to forecast traffic and vehicle conditions, e.g., battery level and congestion. Route planning can then be re-evaluated based on up to the minute information.

EcoGem's Concept & Innovations

While FEVs represent a promising solution for the reduction of fuel consumption, air and noise pollution in urban areas, their commercial viability is at stake if the issues of autonomy are not dealt with in a sufficiently convincing manner. Particularly, the FEV must provide its driver with a high degree of reliability in terms of energy autonomy and efficiency, a difficult task due to the fact that actual autonomy can become unpredictable due to the fragile nature of the vehicle battery, road characteristics, traffic conditions and availability of recharging stations.

It is infeasible to assume that a driver will have the required knowledge to efficiently and effectively manage the energy inflow and consumption of the battery energy while also considering road conditions and access of recharging stations. Therefore, the need for automated and computerized drivers' assistance to take care of all these issues for the drivers would be overwhelming for commercialization of FEVs. To this end, EcoGem's essential objective is to develop an advanced driver assistance system (ADAS) based on the existing work on dynamic GPS-based navigation to automatically manage battery charging, energy saving, and route planning via introducing a new concept of cooperative and intelligent optimization of navigation and energy management. The overall concept can be described and illustrated in Figure-1, where optimization of navigation and energy management is facilitated via V2I (vehicle to centralized infrastructure, responsible for central traffic management) and V2V (vehicle to vehicle) communication links. While the centralized infrastructure has more computing power to deal with larger scale of filtering and optimization tasks upon the timely incoming information, V2V communication provides a low-cost, convenient and instant updates within the traveling neighborhood areas.

Essentially, the EcoGem ADAS will have an embedded communication unit, which automatically records each FEV's traveling experience for every road section traveled in terms of traffic (or speed) and energy consumed. As an example, the traveling experience in terms of traffic could be described in four levels: normal traffic (i.e. close to the standard speed as designated by the road type or its speed limit) encoded as 00; slow traffic encoded as 01; very slow traffic encoded as 10, and extremely slow traffic (almost standstill) encoded as 11. Similar arrangement could also be made for the traveling experience in terms of energy consumptions. Together with the identification code of each specific road section associated, these signals will be automatically transmitted to the centralized infrastructure and other FEVs within its neighborhood areas as shown in Figure 1. For the centralized infrastructure, its powerful computing facilities will automatically process these signals and cluster them via machine learning approaches to produce dynamic weighting parameters for every road section on the basis of timely updating and then transmit these parameters to FEVs. Whenever a driver activates the EcoGem ADAS on his or her FEV by providing his or her intended destination, the EcoGem ADAS will recommend an initially optimized journey plan by taking into consideration of three factors, which include: (i) dynamic parameters made available via V2I communications; (ii) energy required to reach the destination and the energy left inside the battery of the FEV; (iii) the most cost-effective recharging on the journey if required. To ensure the best possible cost effectiveness and reliability, however, such an initial journey plan is subject to changes via the V2V communication as shown in Figure 1. The simplest scenario is the fact that, given the initially recommended journey planning from Bradford to Manchester, as an example, each road section may have just been traveled by other FEV drivers equipped with the EcoGem ADAS, and hence their traveling experiences described by the traffic codes (00, 01, 10, 11) should be shared via their V2V links within certain neighborhood areas. In this way, instant updating and prompt reactions can be facilitated to deal with abrupt events, such as road accidents or natural disasters etc. Since such instant updating is sensitive to the process of timing, a strict filtering or screening must be in place within the EcoGem ADAS in order to ensure its reliability and usability. Examples of such necessity include: (i) a false positive caused by a FEV driver who stopped for taking a break; (ii) a false negative created by the scenario that a road accident is already resolved before the FEV actually arrives at the affected spot. Consequently, while the notion of intelligent optimization in EcoGem is delivered by the machine-learning based and parameter-influenced journey planning, the notion of cooperative optimization is facilitated by such experience sharing through V2V communication and instant updating within the neighborhoods. Therefore, the cooperative optimization of journey planning is essentially implemented in a progressive manner to ensure that any instant updating or correction is robust to any obsolete information or out-of-date experience. In other words, the concept of cooperative optimization introduced by EcoGem is illustrated by gathering and utilising information from near-by EcoGem-enabled vehicles and the EcoGem central platform, as well as revealing and distributing its own information to them. Such cooperative concept will facilitate information sharing and spreading, allowing the in-vehicle EcoGem machine-learning engines to be enriched with instant updates, and thus resulting into more efficient route planning and optimisation.

As a result, EcoGem's approach will be based on the following two primary goals:

1 To render the FEV capable of reaching the desired destination(s) through the most energy efficient route(s) possible.
2 To render the FEV fully aware of the surrounding recharging points/stations while traveling.

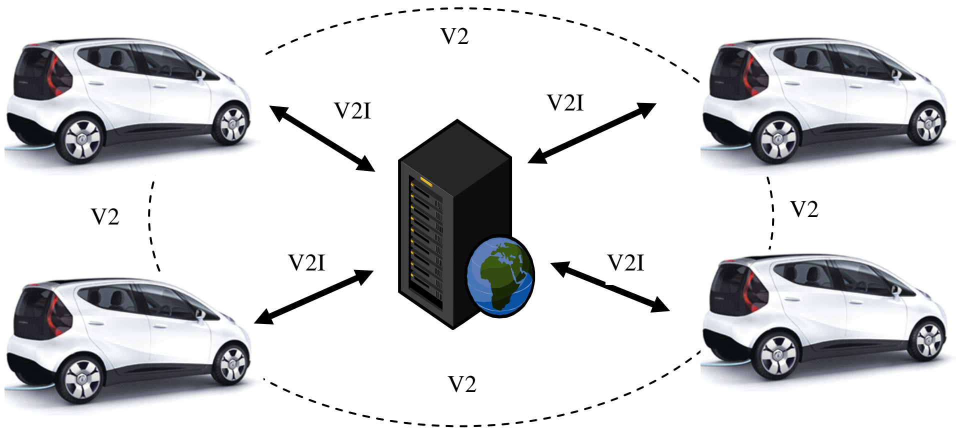

Figure 1: *Illustration of EcoGem concepts*

The first goal will allow for a reduction of the amount of energy spent reaching the driver's desired destinations, leading to an increase in the vehicle's autonomy. Actual reduction rates will vary according to the actual routing options at hand. Nonetheless, significant reduction is expected in cases in which a heavily congested route is avoided, and a noteworthy reduction is also foreseen when a route comprising steep roads is avoided.

The second goal will make the everyday use of an electric car more robust, enabling efficient scheduling of battery recharges and preventing battery depletion while on the move. This is greatly important for a large percentage of plug-in electric vehicles, especially those whose domestic recharging is not an option for their owners or is found insufficient.

EcoGem will innovate and introduce a range of advanced technologies and functionalities. A new, yet untapped, concept is to develop in-vehicle intelligent computing functions and machine learning and reasoning methods to process multi-source information on real-time basis. This will provide tailored driver support via exploitation of past experiences and knowledge, estimation of traffic, optimisation of route planning and optimisation of recharging strategy. EcoGem's vision is, thus, to infuse intelligence and learning functionalities to the FEV, in order to provide enhanced on-board driver support and assistance.

EcoGem intends to realise a significant leap forward compared to the state-of-the-art (SoA), by introducing important innovative ICT-based functionalities and solutions for the Fully Electric Vehicle. EcoGem shall introduce a highly-innovative, unseen before functionality of machine-learning based processing of traffic related information. EcoGem in-vehicle systems will continuously collect traffic measurements as they travel, and utilise them, in conjunction with past experience, so as to automatically classify possible routes to the desired destination according to their degree of congestion, through advanced, machine-learning based processing algorithms. This will enable the in-vehicle driver support and assistance systems to calculate and suggest the best possible routes to the driver.

EcoGem will also be equipped with the ability to automatically detect the need for a recharge on time, and make optimal scheduling recommendations, based on a number of parameters, such as current battery levels, energy consumption rate and other contextual information.

EcoGem's central traffic management platform will be enabled to process multi-source and multi-type information coming from the EcoGem-enabled vehicles, with a view to reaching reliable traffic predictions and ultimately providing effective traffic control and management strategies and enhanced traffic information services. The platform will be enabled to jointly exploit real-time traffic data, historical data, as well as the knowledge extracted from the machine-learning engines of the EcoGem vehicles. It will also be possible to combine this data with traffic data coming as input from legacy traffic monitoring systems.

EcoGem's central traffic management platform will be in position to monitor the status and availability of recharging points, and make this information available to EcoGem FEVs. It will also encompass functionality to assess the impact of power demand on the electrical power supply grid.

Summary

The reduction of fuel consumption and air and noise pollution in urban areas can be realised through the use of Fully Electric Vehicles (FEVs). However, FEVs are not commercially viable if issues of autonomy are not dealt with in a sufficient manner.

EcoGem claims that the success and user acceptability of Fully Electric Vehicles (FEVs) will predominantly depend on their electrical energy management and the corresponding degree of autonomy that they can offer. The motivating factors behind this statement are discussed and the associated problems are addressed. An efficient ICT-based solution equipped with suitable monitoring, learning, reasoning and management capabilities is proposed to help increase the FEV's autonomy regarding the distance that can be traveled before battery depletion and overall electrical energy efficiency. This system will not only be capable of managing the energy consumption of a single vehicle, but through communication with other vehicles and infrastructure, a fleet management system is also described that can also learn from past experiences of other drivers.

The EcoGem concept architecture is provided and roles of intelligent computing functions and machine learning methods are illustrated. A discussion of this original concept emphasises the need for tailored driver support via exploitation of past experiences and knowledge especially when considering estimation of traffic, optimisation of route planning and recharging strategies. A review of the current state-of-the-art in machine learning techniques for in-vehicle intelligence makes obvious the system to be highly adventurous and well beyond the state-of-the-art, yet with feasible objectives.

Main innovations and objectives of EcoGem are concisely described. The implementation plan of EcoGem is discussed and a complete delivery strategy of the project is proposed.

The EcoGem concept is concisely described and explained. The concepts are clearly adventurous, highly motivated for high impact and well beyond the existing state of the art. However, the EcoGem objectives are feasible, specific and supportive for delivering the EcoGem concept, which could ultimately lead to a more energy efficient future.

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References

[1] J. Fawcett and P. Robinson, "Adaptive routing for road traffic," Computer Graphics and Applications, IEEE, vol. 20, pp. 46-53, 2002.

[2] G. A. Godfrey and W. B. Powell, "An adaptive dynamic programming algorithm for dynamic fleet management, I: Single period travel times," Transportation Science, vol. 36, pp. 21-39, 2002.

[3] J. C. McCall, et al., "Lane change intent analysis using robust operators and sparse Bayesian learning," Intelligent Transportation Systems, IEEE Transactions on, vol. 8, pp. 431-440, 2007.

[4] Z. Sun, et al., "On-road vehicle detection: A review," IEEE Transactions on Pattern Analysis and Machine Intelligence, pp. 694-711, 2006.

[5] M. E. Tipping, "Sparse Bayesian learning and the relevance vector machine," Journal of Machine Learning Research, vol. 1, pp. 211-244, 2001.

[6] L. M. Bergasa, et al., "Real-time system for monitoring driver vigilance," Intelligent Transportation Systems, IEEE Transactions on, vol. 7, pp. 63-77, 2006.
[7] D. Chowdhury, et al., "Statistical physics of vehicular traffic and some related systems* 1," Physics Reports, vol. 329, pp. 199-329, 2000.
[8] S. Jung and S. Pramanik, "An efficient path computation model for hierarchically structured topographical road maps," Knowledge and Data Engineering, IEEE Transactions on, vol. 14, pp. 1029-1046, 2002.
[9] L. Kocsis and C. Szepesvári, "Bandit based monte-carlo planning," Machine Learning: ECML 2006, pp. 282-293, 2006.
[10] H. Nakhost and M. M\"uller, "Monte-Carlo exploration for deterministic planning," Proc. 21st International Joint Conference on Artificial Intelligence (IJCAI-09), vol. 1771, 1766.
[11] F. T. Hanshar and B. M. Ombuki-Berman, "Dynamic vehicle routing using genetic algorithms," Applied Intelligence, vol. 27, pp. 89-99, 2007.
[12] J.-Y. Potvin, "State-of-the Art Review Evolutionary Algorithms for Vehicle Routing," INFORMS Journal on Computing, vol. 21, pp. 518-548, 2009.
[13] H. K. Chen, et al., "The real-time time-dependent vehicle routing problem," Transportation Research Part E: Logistics and Transportation Review, vol. 42, pp. 383-408, 2006.
[14] H. Dia, "An object-oriented neural network approach to short-term traffic forecasting," European Journal of Operational Research, vol. 131, pp. 253-261, 2001.