Performance Analysis of a Tour Scheduler Focusing on Time-dependent Gains for Electric Vehicles

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Abstract

After briefly presenting a tour-and-charging scheduler capable of maximizing the time-dependent gains for electric vehicles, this paper conducts an extensive analysis of its performance through a prototype implementation. Main concerns are put on the acquired gain, waiting time, and tour length according to the schedule depth and the number of destinations. Basically, the scheduling service provides an interface for the tour spot manager to upload the time-dependent coupons as well as runs the tour scheduler each time a new request arrives from an electric vehicle. According to the experiment made to run on the real-life geographic tour spot distribution of Jeju City, the proposed scheme takes about 4.8 to 4.9 times as much economic gain as the legacy traveling salesman problem solver. The waiting time approaches the permissible bound specified by the explicit constraint, especially when the schedule acquires more coupons. In addition, the tour length is affected by up to 14.4 %. Here, when many coupons are available, the depth 1 vehicle can monopolize gains, but the next vehicle also takes enough economic gains.

Keywords: electric vehicle, time-dependent gain, tour schedule, schedule depth, waiting time

1. Introduction

Smart grid is a green power system capable of conserving our environment by efficient energy generation, transmission, and consumption. The power system is getting smarter with the combination of computational intelligence. For example, accurate forecast models for energy consumption, renewable energy availability, and the like, allow us to make an efficient energy generation plan, potentially making it unnecessary to burn fossil fuels [1]. In addition, from the consumer side, it is possible to control the operation of each electric device according to well-defined logic taking into account real-time price signal change, current energy load, and other user requirement. More interestingly, recent communication technologies add real-time two-way interaction mechanism between different and heterogeneous smart grid entities. Each entity can quickly catch the change in the power system, cooperate with others, and make decision on the appropriate reaction. Here, through the seamless high-level web interface, a massive number of users can participate in an incorporative decision-making process simultaneously.

Here, many new players are appearing these days. EVs (Electric Vehicles) are penetrating into our daily lives, electrifying the transportation system [2]. Due to their digital nature, they can easily integrate the intelligence of information technologies, mainly in artificial intelligence, optimization, scheduling, and many other sophisticated algorithms [3]. First of all, an intelligent tour plan cannot only reduce the energy consumption but also

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enhance the profit obtained by visiting at a destination during a specific time interval [4, 5]. Many tour spots, shopping malls, and restaurants provide time-dependent coupons and discount plans. However, a coupon is a limited resource, hence, a coupon is taken by an EV, other EVs cannot use it. This situation is the same as the case a charger is reserved by an EV and others cannot use it during the reserved time interval [6]. Here, the visiting sequence is important for the schedule quality and can be decided taking advantage of a bunch of already existing well-known computer algorithms [7].

This paper presents a reservation-based coupon system for EVs and measures its performance, mainly comparing with the legacy TSP (Traveling Salesman Problem) solver [8]. Our EV information service generates a tour schedule maximizing the benefit while meeting the requirement on waiting time and tour length [9]. Then, if valid coupons are assigned to EVs, the service will modify the coupon availability table. The next tour schedule requested from another EV will be created with the updated coupon table. The coupon allocation is repeated until the last requester. Here, the tour generator, as a variant of a TSP solver, traverses the search space, evaluates a schedule reaching at a leaf node, and finds the best one in terms of the total gains [10]. During the traversal, the subtree violating the waiting time constraint will be cut down. On each evaluation, if the solution is better than the current best, it will replace the current best. After the traversal, the best solution survives.

The scheduler processes each request one by one. Hence, the calling order is very important to the user-side satisfaction. For the scheduler to be more applicable to the real-life, it is important to make sure that it works efficiently also after many coupons are allocated. As an extended version of our previous work [11], this paper first gives more details on the tour scheduling service architecture embracing coupon providers, EV drivers, database, and the scheduler. Then, extensive experiment results will be demonstrated and analyzed focusing on waiting time and tour length according to the schedule depth. Here, the waiting time is the time interval during which an EV must wait due to insufficiency in its battery energy to reach the next destination. The tour length increases to additionally visit a charging station during the tour. Charging at a station far away from the tour route must be avoided, if possible.

This paper is organized as follows: After outlining the whole paper in Section 1, Section 2 introduces related work on tour schedulers for EVs. Section 3 describes the architecture of the EV tour scheduler and the interaction between each entity. Section 4 conducts the analysis on economic gain, waiting time, and tour length. Finally, Section 5 summarizes and concludes this paper with a brief introduction of future work.

2. Related Work

[12] handles an interesting and unique problem of jointly optimizing the goals in scheduling and charging of EVs. Those parameters given in their problem consist of a set of preconstructed tours, a fleet of both EVs and gasoline-powered vehicles, and a charging infrastructure. Their scheme allocates vehicles to tours, while the allocation goals are to maximize the use of EVs and to minimize the overall charging cost. The authors formulate this problem by a mixed-integer linear programming model, defining essential constraints to find an optimal allocation. For example, overlapped tours cannot be allocated to a single vehicle, an EV cannot be charged during its tour, the total power cannot exceed the provisioned amount, and so on. This model further analyzes several business scenarios such as reduction of CO_2 emissions, diversity of EV models, avoidance of EV battery degradation by repeated use, and optimization of the charging infrastructure.

[13] presents an optimization method in the energy management of a PHEV (Plug-in Hybrid Electric Vehicle) taking advantage of a trip prediction scheme. For a given itinerary, the vehicle speed and thus the energy consumption will be different due to many non-deterministic factors of driving. A PHEV alternates EV and CS (Charge-Sustaining)

modes mainly according to the vehicle speed. Hence, which mode to take at each moment is critical to the fuel energy consumption and the SoC level management. Here, the speed prediction can be conducted by a speed profile created by Markov chains taking the previous trip records as input. A vehicle-level controller is implemented, embedding a forward-looking Powertrain model. Even though this scheme is built originally for PHEV, EV models can also employ the SoC (Status-Of-Charger) estimation method, especially when there are many unpredictable features even for the same route such as stop positions, average speeds, speed limits on a road, and the like [14].

Next, considering the still immature reliability of EVs for delivery services, [15] proposes a route disruption management scheme which deals with unavailability of a vehicle visiting multiple destinations along a predefined route. Here, each EV is assigned to a district and delivers items to each destination inside the district. The destinations within the district of a failed vehicle must be reallocated to other vehicles. Namely, the visiting sequence of the failed EV needs to be broken into several subsequences and reallocated. The objective is to minimize the operational costs while serving the total demand as well as not violating the limit imposed on the working time and vehicle load capacity. The management system predefines a back-up district, which can be more easily split than others. In case of detecting a failure, the EV in this district will be dispatched to the failed district and the back-up district will be reassigned. The problem formulation designates just one district as the back-up and a vehicle operator can leave its predefined route at most once. Now, a linear program model takes each requirement to solve this problem, defining a variety of binary variables to denote whether a district is the back up, whether a segment (destination) is assigned, which vehicle is relocated, and the like.

3. Tour Scheduler Service

Figure 1 depicts the service architecture of our tour scheduler. A POI can be registered to the system with the specification on its location, POI type, and other features, according to the contract procedure. It includes enrollment fee payment, POI validation, and final membership endorsement. A POI can upload its coupons to the coupon database. Basically, a coupon table contains the validity interval, offered gain, and the like. The tour scheduler maintains a road network by which the cost between two points can be estimated. The cost can be tour time, tour distance, and battery consumption. For a set of destinations, the tour scheduler builds a cost matrix and runs the TSP solver based on the evaluation function for a route. Now, an EV driver submits the set of tourist spots. In response to this request, the scheduler finds the schedule, or visiting sequence, which maximizes the coupon gain without the violation of the constraints on the waiting time [16]. If the EV accepts the schedule, the coupon table is updated, namely, the allocated coupon is removed.
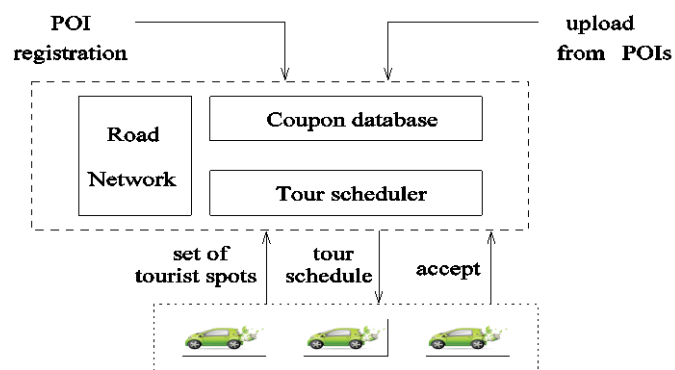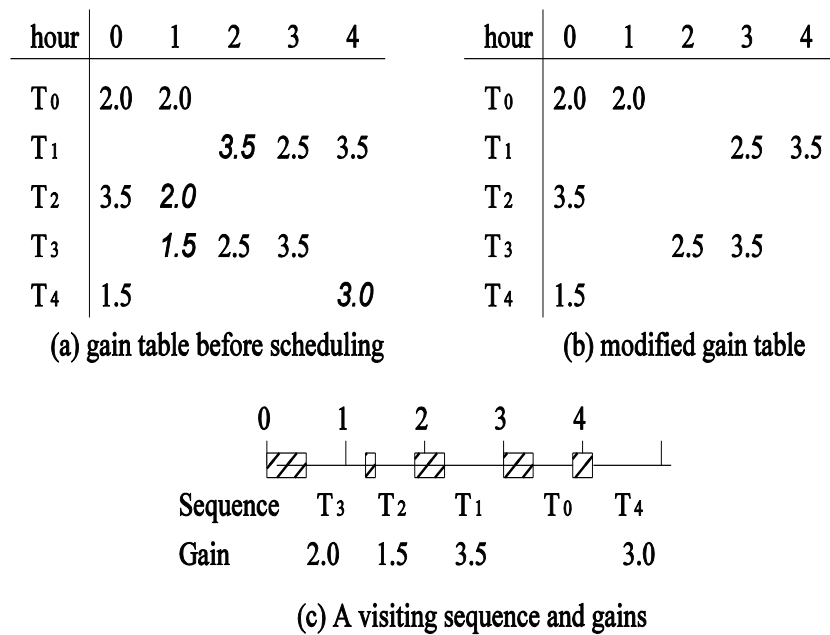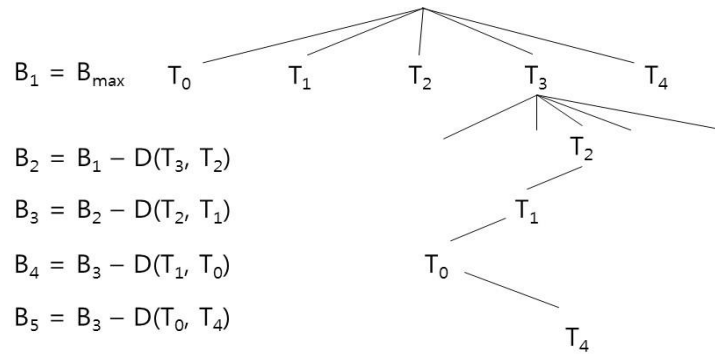

Figure 1. Scheduling Procedure

Now, Figure 2 illustrates the operation of our scheduler for a request by an example. An EV specifies the set of 5 destinations from T_0 to T_4. Then, the number of feasible sequences will be 5!. For a sequence, we can know the time interval during which the EV stays at each destination according to the driving distance and standard vehicle speed. Here, the time axis is divided into fixed size slots for a deterministic response time. Then, the scheduler checks if a destination offers a coupon at that time interval. The sum of all gains acquired by visiting at a destination at the time offering a valid coupon is the total gain. In Figure 2 in which the visiting sequence is decided as $(T_3, T_2, T_1, T_0, T_4)$, the EV arrives at each of them during time slots 0, 1, 2, 3, and 4, respectively. Figure 2(a) is the coupon table before scheduling and Figure 2(b) after scheduling. The coupons marked italic, namely, T_2 at time slot 1, T_3 at slot 1, and T_1 at slot 2 offer valid gain. In Figure 2(c), shaded boxes denote the intervals for driving. Here, the EV stays at T_3 across slots 0 and 1, expecting coupons associated with T_3. But, T_3 provides no coupon in slot 0. Next, the EV stays at T_2 during slot 1, taking the coupon worth 1.5. The currency will be USD, but it doesn't matter which one will be selected.

hour	0	1	2	3	4
T_0	2.0	2.0			
T_1			*3.5*	2.5	3.5
T_2	3.5	*2.0*			
T_3		*1.5*	2.5	3.5	
T_4	1.5				*3.0*

(a) gain table before scheduling

hour	0	1	2	3	4
T_0	2.0	2.0			
T_1				2.5	3.5
T_2	3.5				
T_3				2.5	3.5
T_4	1.5				

(b) modified gain table

	0	1	2	3	4	
Sequence	T_3	T_2	T_1	T_0	T_4	
Gain		2.0	1.5	3.5		3.0

(c) A visiting sequence and gains

Figure 2. Scheduling Procedure

Figure 3 shows the search space of the tour scheduler. The traversal procedure begins from the root and fills each tree node with a destination one by one. From the route the first level node can be T_0 to T_4. At the level 1 nodes, the battery is fully charged, namely, the current battery at level 1, B_1, is set to B_{max}. Next, a second node is selected one by one except the first node of the subtree. Then the current battery at level 2 reduces by the amount of electricity consumed for driving from the first level destination and the second level destination. We can employ any battery consumption model for this purpose. If the remaining battery is not enough to reach the next destination, the subsequent node expansion has no meaning, hence the subtree is pruned. Figure 3 shows the expansion of the space search tree for the sequence of $(T_3, T_2, T_1, T_0, T_4)$. Only those solutions surviving the battery constraint will be evaluated in terms of the total gains. This expansion procedure can significantly enhance the response time by avoiding wasteful node expansion especially when the number of destination gets larger and the tour schedule gets tighter.

$B_1 = B_{max}$ T_0 T_1 T_2 T_3 T_4

T_2

$B_2 = B_1 - D(T_3, T_2)$

$B_3 = B_2 - D(T_2, T_1)$ T_1

$B_4 = B_3 - D(T_1, T_0)$ T_0

$B_5 = B_3 - D(T_0, T_4)$

T_4

Figure 3. Search Space Tree

4. Performance Measurement

This section measures the performance of the tour scheduler via prototype implementation, focusing on coupon gain, waiting time, and tour length, according to the schedule depth and the number of destinations. Initially, the coupon is not allocated to an EV and the first request, which has the schedule depth 1, can fully take as many coupons as possible. Then, the next requester has fewer coupons than the first. For each experiment, 20 different sets are generated and their results are averaged. In a tour spot generation, stay time, inter-destination distance, and coupon value distribute exponentially with their own averages. Here, the averages of the stay time, the coupon availability, and the coupon value are set to 20 minutes, 0.2, and 20.0 (USD), respectively. In addition, we put a constraint that the waiting time must not exceed 30 minutes. The amount of permissible waiting time can be an experiment parameter, but it's not considered as it is not so much relevant to coupon gains. We assume that all vehicles want to visit the same set of destinations only for simplicity and performance evaluation, but this restriction can be removed without loss of generality.

Figure 4 plots the total gain according to the schedule depth, while the number of destinations is fixed to 9. 9 destinations are picked from the map of Jeju City, Republic of Korea. The schedule depth denotes the order the request is processed. For the first vehicle, the total gain of our scheme is 125.04, while that of the TSP solver is 25.73. This result indicates that even though the tour length may increase, the economic benefit increases by 4.9 times. For the second vehicle, the gain reaches 92.2. Not so much as the case of the first vehicle, the gain is larger than the TSP solver by 4.8 times. For the 5th vehicle, for which just a few coupons are available, both schemes have no coupon gains. Only for the 3rd vehicle, the TSP solver is temporarily better than the proposed scheme because more coupons are left after 2 vehicles are scheduled. The legacy distance-based tour scheduler cannot collect coupons even in the case of sufficient availability, as can be inferred from the rather flat behavior of the gain curve.
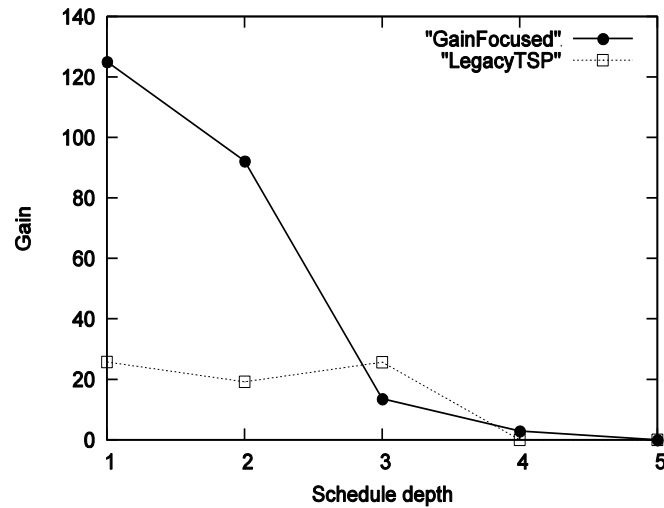
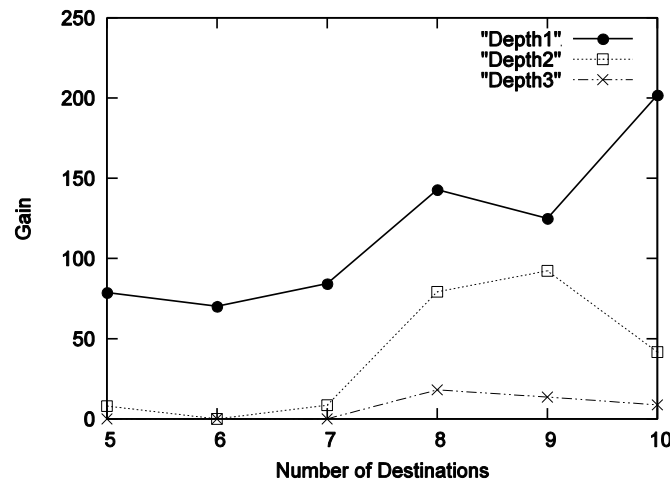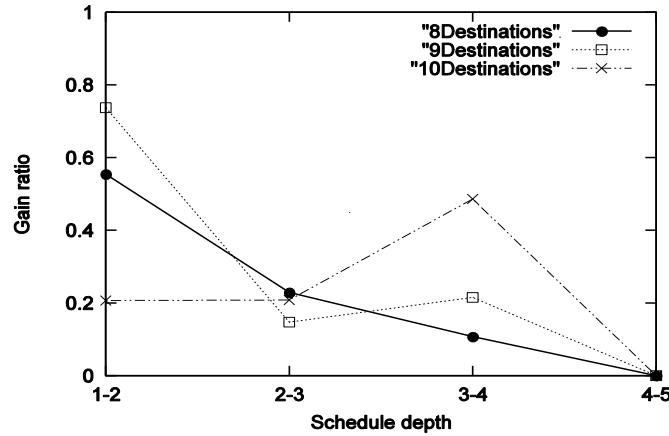**Figure 4. Gain vs. Schedule Depth**



Figure 5. Gain vs. Number of EVs

Next, Figure 5 shows the coupon gains for 1st, 2nd, and 3rd vehicles, according to the number of destinations ranging from 5 to 10. For 7 or fewer destinations, the available coupons are also not so sufficient and almost all coupons are assigned to the first vehicle. Hence, the subsequent vehicles get nothing. Here, the number of visiting sequences is limited, so the second or later vehicles have not so many tour options not violating the given constraint. On the contrary, for from 8 to 10 destinations, the second vehicle also gets 20 to 73 % gain of the first vehicle. The third vehicle gets from 14 to 22 % of its predecessor, namely, the second vehicle. The fourth or later vehicles hardly obtain time-dependent profits. Judging from Figure 5, the total gain largely seems proportional to the number of destinations and coupon availability. But the curve is not smooth. The gain depends on the tour schedule and more radically on the geographic distribution of selected destinations [17]. As we make the pure tour length range from 100 to 120 *km*, a specific group of destinations tends to be selected more often. The distribution of those destinations has quite much impact on the total gain.

Figure 6. Gain Ratio vs. Schedule Depth

Figure 6 shows the ratio of the total gain between two requests whose schedule depths differ by 1. It measures how much the precedent schedule affects its successor. In the case of 8 destinations, the gain ratio decreases a little bit linearly. For 9 destinations, the EV of schedule depth 1 takes not so many coupons, leaving them to its next successor, which takes about 74 % of the depth 1 EV. Obviously, the successor of an EV which has taken many coupons cannot but acquire a smaller gain ratio than average. In the case of 10 destinations, the depth 1 EV monopolizes the economic benefit as can be inferred from that 1-2 ratio is only 0.2. Finally, as the depth-5 vehicle rarely takes any coupon, the 4-5 ratio is zero for all curves. We think if the assumption that the destination set of every vehicle is the same is removed, the result will be different, as the coupons obtainable by each EV will not be concentrated.

Now, the performance metric is changed to waiting time. If an EV doesn't have enough electricity to reach the destination in the subsequent sequence, it should wait until it gets the needed energy on a charging station [18]. The EV is forced to wait without doing anything. As the legacy TSP hardly entails the additional drive, the waiting time remains at zero as shown in Figure 7. Here, the experiment parameters are selected as in Figure 4. On the contrary, this figure reveals that the economic gain does not come free. The waiting time approaches the permissible bound, namely, 30 minutes. When there is almost no gain, namely, when the scheduling depth is equal to or larger than 4, the waiting time will be zero. For the scheduling depth of 3, the waiting time gets abnormally higher in spite of just a small gain. Even though with the deployment of DC chargers, the waiting time can be disregarded in the future, the charging infrastructure does not yet reach the full coverage.
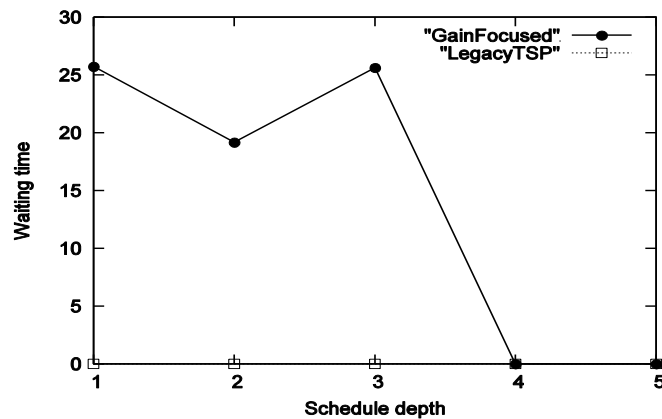
Figure 7. Waiting Time vs. Schedule Depth

Figure 8 plots the waiting time according to the number of destinations. This figure has 3 curves for the depth of 1, 2, and 3, respectively. As mentioned previously, the depth 1 case usually has the largest gain. But, its waiting time can be reduced, achieving two goals of more gains and smaller waiting time simultaneously. For up to 7 destinations, the waiting time is negligible. With 8 destinations, the difference between 3 cases is less than 5 minutes, indicating that the coupons are quite evenly allocated to EVs. In the case of 9 destinations, only the waiting time of depth 2 case is less than the others by 6 minutes. Here, a better gain may bring a worse waiting time. However, with 10 destinations, the coupon availability is highest. The first vehicle monopolizes profitable coupons along its route, hence its tour length and waiting time is not affected. Even though the next depth EVs also benefit from the better availability, the waiting time of the depth 1 EV gets to near 2 minutes.
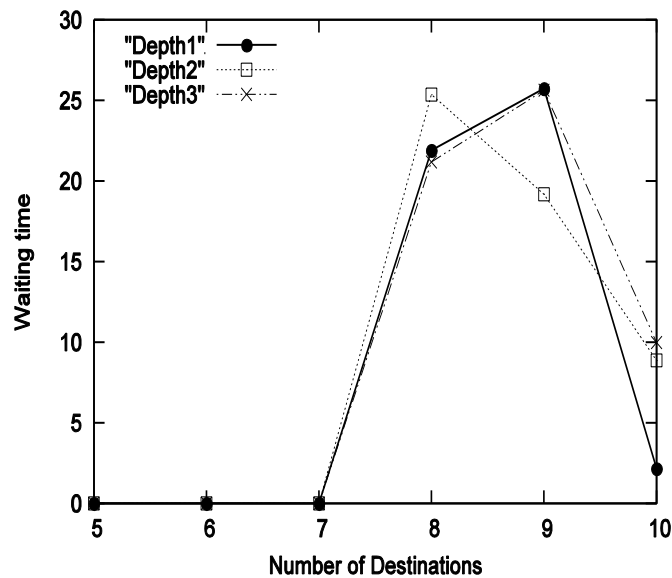
Figure 8. Waiting Time vs. Number of EVs

Figure 9 and Figure 10 measure the effect of the gain-focused tour schedule to the tour length [19]. Here, the number of destinations is set to 9. Without charging, the tour length will include just the distance between each pair of two destinations adjacent in the visiting sequence. In addition, the visiting order can be different from the distance-optimal one to visit a spot at a specific time interval. The tour length leads to the increase in the tour time as well as the waiting time. In Figure 8, the tour length is constant for the legacy TSP irrespective of the schedule depth as it takes just the driving distance into account. For the depth 1 EV in the proposed scheme, the tour length increased by 13.9 %, that is, the distance-optimal sequence is changed in order to get more time-dependent gains. For 2 and 3 vehicles, the tour length also increases by 14.4 and 12.8 %, respectively, but the coupon gains for these cases are not so many as the depth 1 EV.
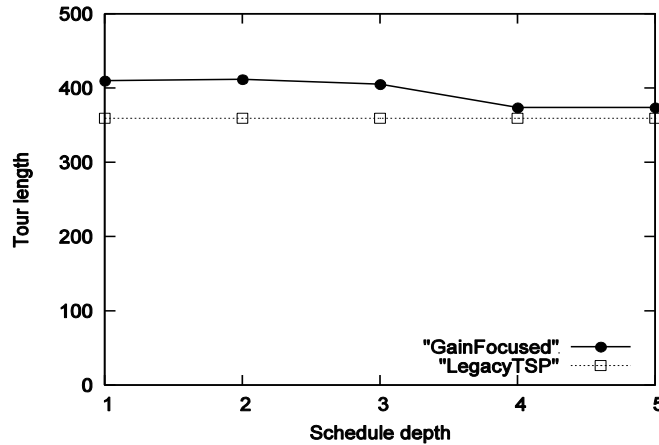
Figure 9. Tour Length vs. Schedule Depth

Finally, Figure 10 shows the tour length according to the number of destinations for 3 EVs of depth 1, 2, and 3, respectively. The number of destinations ranges from 5 to 10 in this experiment, while other parameters are the same as the previous experiments. For each number of destinations, the tour length gap between different schedule depths ranges from 0.2 to 22 minutes for a daily tour. Here, the average vehicle speed is assumed to be 60 *km/h*. The TSP distance is commonly made to range from 100 to 150 *km*, a little bit broader to get more diverse destination sets. However, according to the increase in the number of destinations, the total stay time at respective destinations also increases. Hence, the tour length largely increases along with the number of destinations. The tour length difference reaches 5.2 % for 9 destinations. This figure indicates that the tour length shows quite a stable behavior, having no unexpected peak and remaining in the predictable range, even if we can get the economic gain efficiently.
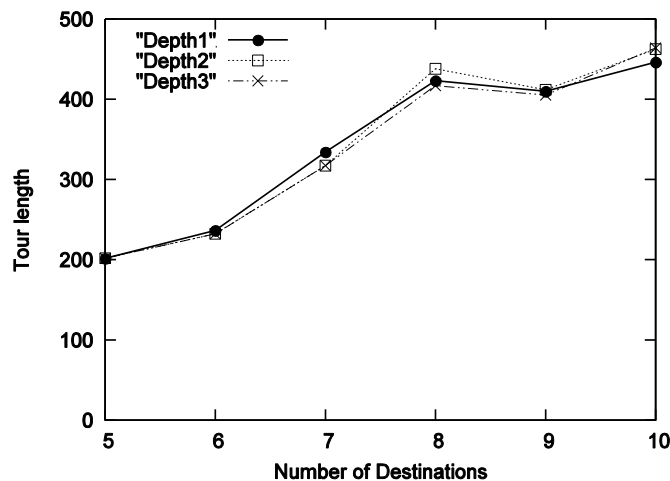

Figure 10. Tour Length vs. Number of Destinations

5. Conclusions

Due to their digital nature, EVs can integrate sophisticated information and communication technologies better than any other smart grid objects. In this paper, we have presented a time-dependent coupon management mechanism and designed a tour scheduler capable of maximizing gains, taking advantage of computational intelligence in TSP algorithms. As many EVs will send schedule requests to the server, it is necessary to

understand the behavior of the scheduler according to the request order, namely, the schedule depth. Hence, coupon gain, waiting time, and tour length are extensively investigated according to the schedule depth and the number of destinations, through a prototype implementation. The Jeju area map is used for tour spot distribution.

According to the experiment result, the proposed scheme works even when only a few coupons are left after several allocations, overcoming the scarcity of the resource. Basically, it takes about 4.8 to 4.9 times as much economic gain as the legacy TSP solver for the meaningful schedule depth range. The waiting time approaches the permissible bound specified by the explicit constraint, especially when the schedule acquires more coupons. In addition, the tour length is affected by up to 14.4 %. Here, when many coupons are available, the depth 1 vehicle can monopolize gains, without increasing the tour length, as it can take from the location just next to its tour route. However, the next vehicle also takes enough, compared with the legacy TSP solver.

As future work, we are planning to combine the tour scheduler with a variety of information sources as many as possible. To begin with, the charger status stream is the first candidate, as a tour schedule cannot but depends on the availability of chargers. Without the accurate information on whether a charger is not occupied on a specific time interval, the tour schedule may bring unexpected waiting time. The charging infrastructure currently under construction essentially provides the capability of real-time management by exchanging messages with a central or autonomous control system through proper communication channels over the community area [20]. Such data analysis, possibly executed on a big data platform will distribute EVs over the service area, making it possible to assign EVs to chargers according to a specific system goal. This strategy can enhance the user-side satisfaction and balance the power load. Moreover, data fusion will create a new business model in smart grids.

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