Proceedings of the 17th World Congress
The International Federation of Automatic Control
Seoul, Korea, July 6-11, 2008

# Hybrid Predictive Control for the Vehicle Dynamic Routing Problem based on Evolutionary Multiobjective Optimization (EMO)

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**Abstract:** In this paper, a hybrid adaptive predictive control approach (HAPC) to solve a dynamic pickup and delivery problem (DPDP) is presented based on a dynamic objective function that includes two dimensions: user and operator costs. Because these two costs are opposite components, the problem was formulated and solved by using an Evolutionary Multiobjective Optimization (EMO) technique. The idea is to minimize both, user and operator costs. At every instant, the use of genetic algorithms is proposed to find the optimal Pareto front associated with the DPDP, whose Pareto Optimal set is a set of solutions of the problem. Since only one solution has to be applied to the system every time a new request appears, several criteria will be utilized in order to properly use the information provided by the dynamic optimal Pareto front. Illustrative experiments through simulation of the process are presented to show the potential benefits of the new approach. Thus, by using EMO, the trade off between the two conflicting objectives will become clear for the dispatcher when making dynamic routing decisions.

## 1. INTRODUCTION

The dynamic pick up and delivery problem (DPDP) was formulated by a set of requests of passengers traveling from an origin (pick up) to a destination (delivery) served by a fleet of vehicles located initially at several depots (Desrosiers *et al.*, 1986; Savelsbergh and Sol, 1995). The dynamic dimension of the problem arises when a subset of requests is not previously known and dispatch decisions must be conducted in real time. Progress in communication and information technologies in the last few years has allowed researchers to formulate this kind of dynamic problem and develop efficient algorithms of high computational complexity to optimize dispatcher decisions in real time. When the problem is dynamic, a well-defined objective function must consider the prediction of future demand and consequently, of the passengers' waiting and travel times in the system due to potential rerouting decisions, issues normally not considered in the specialized literature. In addition, proper specification includes a prediction of the traffic conditions of the system, in space and time, to get more realistic estimations of travel time of the vehicles. This additional source of uncertainty has not been extensively treated in the specialized literature, due mainly to its computational complexity.

Regarding dynamic routing decision models including prediction, only a few efforts have been devoted to develop models that use information systems about future events to make better real-time routing decisions (Ichoua et al., 2005; Topaloglu and Powell, 2005). Sáez et al. (2007) and Cortés et al. (2007) developed an analytical formulation for the DPDP problem as a hybrid adaptive predictive control problem (HAPC) using state space models and algorithms that come from the computational intelligence literature (Genetic Algorithms (GA) and Fuzzy Clustering). In that work, the authors demonstrated that GA is an effective algorithm for solving real-time instances of the problem. A reasonable definition of a predictive objective function should include both operator and user costs, as a function of the estimated travel time for vehicles and users as well as waiting time for passengers before they are picked up. The dynamic nature of the problem forces the modeller to include the effect of potential rerouting in actual dispatch decisions as part of the objective function. Such a formulation should properly quantify the impact on the users' level of service affected by these decisions, as well as on the associated additional operational costs. These decisions were made within a context of unexpected traffic conditions which could interfere with the operation of the vehicles under dispatch rules (Cortés et al., 2007).

These two dimensions considered in the system objective function are opposite objectives. On the one hand, the interest of the operator is in minimizing operational costs, and, on the other, the users want to obtain good service. In fact, offering a better level of service implies more direct trips, resulting in lower vehicle occupancy rates and consequently, higher operational costs to satisfy the same demand with a fixed fleet. More efficient routing policies from the operator's standpoint will reflect higher occupation rates, longer routes, and consequently, longer waiting and travel time for users. Thus, the question is how to properly balance both components of the objective function to make proper planning and fleet dispatching decisions. The answer is not clear. It depends on who makes the decisions and in what context. To guide the dispatch process, in this paper we propose a multiobjective approach to give the DPDP more general treatment based on the formulation of the problem under a HAPC approach by Cortés et al. (2007). In the present work Evolutionary Multiobjetive Optimization (EMO) was used to solve the dynamic formulation of the DPDP, considering both opposite dimensions (operator and users) in the objective function.

Mainly the solution of static problems has been conducted in the EMO literature. There is an interesting work done by Tan et al. (2007), where a multiobjective stochastic vehicle routing problem is solve via EMO. Literature on dynamic EMO problems is scarce and it lacks clear evaluation methodologies (Farina et al., 2004). In the application of multiobjective techniques in conventional Model Predictive Control (MPC), some interesting contributions are Alvarez and Cruz (1998), Kerrigan and Maciejowski (2002), Laabidi and Bouani (2004) and recently Subbu et al. (2006).

Regarding Hybrid Predictive Control (HPC) and EMO, Kerrigan et al. (2000) present several methods for handling a large class of multiobjective formulations and prioritizations for model predictive control of hybrid systems, using the Mixed Logic Dynamical (MLD) framework. The methods are flexible and systematic, and use propositional logic and the MLD modelling for prioritizing soft constraints in MPC and guaranteeing inclusion of the maximum number of hard constraints.

In this paper, the model by Cortes et al. (2007) is reformulated under a dynamic EMO view. The use of EMO allows the decision-maker to obtain solution, which are not explored with the typical HAPC to solve the DPDP problem. This extra information is a crucial support for the decision-maker who is searching for reasonable options of service policies.

The problem is presented below, and the formulation of the proposed predictive objective function (mono-objective) is stated. In Section 3 the EMO formulation is proposed. In Section 4 results by simulation are shown and analyzed, and finally conclusions and future work are highlighted.

## 2. PROBLEM FORMULATION

### *2.1. HAPC for DPDP and dynamic model formulation.*

Under a dial-a-ride operation system, where people ask for a door-to-door service, suppose a fleet size of $F$ vehicles. The specific location of a request (which includes its pickup as well as its delivery) is known only after the associated call is received by the dispatcher. A selected vehicle is then rerouted at real time to insert the new request into its predefined route (sequence) while the vehicles are in motion. The assignment of the vehicle and the insertion position of the new call into the previous sequence of tasks associated with such a vehicle, are control actions decided by the dispatcher (controller) based on the objective function, which depends on the variables related to the state of the vehicles in real time. The fleet is in operation travelling within the influence area according to predefined routes. The service demand $\eta$ is unknown, it appears in real time and it is characterized by two positions, pickup and delivery, and by the instant of the call occurrence. The modelling approach is in discrete time, where the steps are activated every time a relevant event occurs, for example when a call asking for service is received. $k$ represents the $k^{th}$ instant in the discrete events sequence. The predictive model is formulated in terms of three state space variables: estimated time of arrival to a stop, vehicle load between stops, and the vehicle position. In order to compute these variables, we consider two sources of stochasticity. The first regarding the unknown future demand entering the system in real time, and the second coming from the network traffic conditions, in its spatial and temporal dimensions. At any instant $k$, every vehicle $j$ is assigned a sequence of tasks, which includes several points of pickup and delivery. Those sequences can be represented by the function

$$S_j(k) = \left[ s_j^0(k) \quad s_j^1(k) \quad \cdots \quad s_j^i(k) \quad \cdots \quad s_j^{w_j(k)}(k) \right]^T ,$$

where the $i^{th}$ element of the sequence represents the $i^{th}$ stop of vehicle $j$ along its route, and $w_j(k)$ is the number of stops associated. A stop is defined by a coordinate and a user who requires the service. The initial condition $s_j^0(k)$ corresponds to the last satisfied request. The set of sequences $S(k) = \left\{ S_1(k), ..., S_j(k), .., S_F(k) \right\}$ associated with the fleet of vehicles correspond to the control (manipulated) variable $u(k)$. The proposed HAPC dispatcher selects the optimal sequences based on the minimization of an ad-hoc objective function. Thus, a sequence of stops assigned to vehicle $j$ at instant $k$, $S_j(k)$, is given by:

$$S_j(k) = \begin{bmatrix} z_j^0(k) & P_j^0(k) & r_j^0(k) & \Omega_j^0(k) \\ z_j^1(k) & P_j^1(k) & r_j^1(k) & \Omega_j^1(k) \\ \vdots & \vdots & \vdots & \vdots \\ z_j^{w_j(k)}(k) & P_j^{w_j(k)}(k) & r_j^{w_j(k)}(k) & \Omega_j^{w_j(k)}(k) \end{bmatrix} \quad (1)$$

where $z_j^i(k)$ equals 1 if the stop $i$ is a pickup and equals 0 if it is a delivery, $P_j^i(k) \in R^2$ is the geographic position in spatial coordinates of stop $i$ assigned to vehicle $j$, $r_i^j(k)$ identifies the passenger who is making the call and $\Omega_j^i(k)$ is the number of passengers associated with the request. Figure 1 shows a sequence assigned to vehicle $j$ at instant $k$, which corresponds to the tasks assigned to a vehicle.

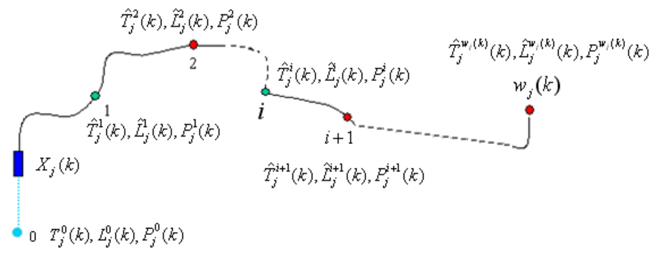


Fig. 1. Representation of sequence of vehicle $j$ and its stops.

$\hat{T}_j^i(k)$, $\hat{L}_j^i(k)$ and $X_j(k)$ represent the expected departure time, the expected load and the actual position of vehicle $j$ from stop $i$, at instant $k$. The real distribution of speeds is assumed to be unknown (denoted by $v(t,p,\varphi)$) which depends on a stochastic source $\varphi(t)$, representing the traffic conditions of the network, and of a $p$ function defined by the straight line that joins two consecutive stops. Besides, a speed distribution for the urban zone during a typical period of recurrent congestion, represented by a speed model $\hat{v}(t,p)$, is supposed to be known, which can be obtained from historical speed data.

The closed loop of the dynamic vehicle routing system is shown in Figure 2. The HAPC represented by the dispatcher makes the routing decisions in real time based on the information it has about the system (process) and in the values of the vehicle fleet attributes, which allow evaluating the model under different scenarios. Demand ($\eta_k$) and traffic conditions ($\varphi(t_k)$) are disturbances in this system. An adaptive mechanism for the proposed control is added in Figure 2, to modify the objective function according to demand and traffic predictions, which can vary in time.

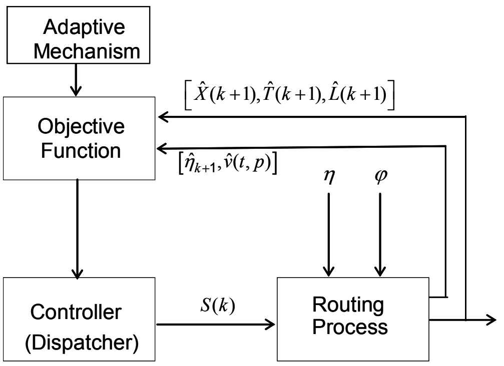


Fig. 2 Closed loop diagram of the HAPC for DPDP.

To apply the HAPC approach, a dynamic model is proposed to represent the routing process.

The dynamic model for the position of vehicle $j$ is as follows,

$$\hat{X}_j(k+1) = P_j^0(k) + \int_{t_k}^{t_k+\tau} \hat{v}(t,p(t)) \frac{\left(P_j^0(k) - P_j^1(k)\right)}{\left\|P_j^0(k) - P_j^1(k)\right\|_2} dt \qquad (2)$$

where $t_k \le t \le t_k+\tau$. $t_k$ is a variable that links the continuous time with the discrete time ($k$) associated with the modeling scheme. The variable time $\tau$ is defined by the interval between the occurrence of the future probable call at instant $t_k+\tau$ and the occurrence of the previous call at $t_k$. $\tau$ is calculated as a tuning parameter for the HAPC.

The model for the predicted departure time vector is:

$$\hat{T}_j(k+1) = \left[ T_j^0(k) \quad t_k + \kappa_j^1(k) \quad .... \quad t_k + \sum_{s=1}^{w_j(k)} \kappa_j^s(k) \right] \qquad (3)$$

where $\kappa_j^i(k)$ is an estimation of the time interval between stop $i$-$1$ and stop $i$ for the sequence of vehicle $j$ at instant $k$, which depends on $\hat{v}(t,p)$.

The dynamic model associated with the vehicle load vector depends exclusively on the current sequence and its previous load. Analytically, we have:

$$\hat{L}_j(k+1) = \Big[ L_j^0(k) \quad L_j^0(k) + (2z_j^1(k)-1)\Omega_j^1 \quad .... \qquad (4)$$
$$L_j^0(k) + \sum_{s=1}^{2}(2z_j^s(k)-1)\Omega_j^s \quad .... \quad L_j^0(k) + \sum_{s=1}^{w_j(k)}(2z_j^s(k)-1)\Omega_j^s \Big]^T$$

where $z_j^s$ and $\Omega_j^s$ were defined in (1). The proposed vehicle sequences and state variables satisfy a set of constraints given by the real conditions of the DPDP problem. Specifically, we must consider constraints of precedence, capacity and consistency in the solution of the HAPC problem to generate only feasible sequences.

*2.2 Objective Function.*

The objective of the HAPC is to minimize an objective function from which the best routes for the vehicles will be selected. The proposed objective function quantifies the costs over the system of accepting the insertion of a new request. Such a function incorporates two decision dimensions, which normally move in opposite directions. The first component is the users' cost which includes both waiting and travel time experienced by each passenger. The second component is the cost associated with the operation of vehicles. In this approach, the latter cost incorporates two types of expenses: the cost per traveled distance unit and the cost spent by operating the vehicles in time units. A fixed fleet size is considered.

A reasonable prediction horizon $N$ is defined, which depends on the problem in study and on the intensity of unknown events, which can occur in the system in real time. The controller will compute the decisions for the complete control horizon $N$, namely $S_k^{k+N} = \{S(k), ..., S(k+N\text{-}1)\}$, considering the predictions based on historical data, and will apply only the sequence decided for the current instant $S(k)$ to the system according to the receding horizon method. The performance of the vehicle routing scheme will depend on how well the objective function can predict the impact of possible rerouting, due to insertions caused by unknown service requests. Analytically, a mono-objective version of the proposed objective function for a prediction horizon $N$, can be written as follows:

$$\underset{S_k^{k+N}}{Min} \ \lambda J_1 + (1-\lambda) J_2 \qquad (5)$$

$$J_1 = \sum_{\ell=1}^{N} \sum_{j=1}^{F} \sum_{h=1}^{h_{\max}(k+t)} p_h(k+\ell)\left(J_j^U(k+\ell) - J_j^U(k+\ell-1)\right)$$

$$J_2 = \sum_{\ell=1}^{N} \sum_{j=1}^{F} \sum_{h=1}^{h_{\max}(k+t)} p_h(k+\ell)\left(J_j^O(k+\ell) - J_j^O(k+\ell-1)\right)$$

$$J_j^O(k+\ell) = \sum_{i=1}^{w_j(k+\ell)} \left(c_T\left(\hat{T}_j^i(k+\ell) - \hat{T}_j^{i-1}(k+\ell)\right) + c_L D_j^i(k+\ell)\right) \qquad (6)$$

$$J_j^U(k+\ell) = \sum_{i=1}^{w_j(k+l)} \Bigg( \underbrace{\theta_v \hat{L}_j^{i-1}(k+\ell)\left(\hat{T}_j^i(k+\ell) - \hat{T}_j^{i-1}(k+\ell)\right)}_{J \text{ TRAVEL TIME}} \qquad (7)$$
$$+ \underbrace{\theta_e z_j^i(k+\ell)\left(\hat{T}_j^i(k+\ell) - T_j^0(k+\ell)\right)}_{J \text{ WAITING TIME}} \Bigg)$$

where $J_j^U$ and $J_j^O$ denote the user and operator costs respectively, associated with the sequence of stops that vehicle *j* must follow at certain instant. In equations (5)-(7), $k+\ell$ is the instant at which the $\ell^{th}$ request enters the system, measured from instant *k*. $h_{\max}(k+\ell)$ is the number of possible requests at instant $k+\ell$, $p_h(k+\ell)$ is the probability of occurrence of the $h^{th}$ request, associated with a trip pattern related to a specific pair of zones. The occurrence probabilities associated with each scenario are parameters in the objective function and must be calculated based on real time or historical data, or a combination of both. In this work, a zoning based on Fuzzy Clustering proposed in Sáez *et al.* (2007) was designed. Expressions (6) and (7) represent the operator and users cost functions related to vehicle *j* at instant $k+\ell$, which depend on the previous sequence and a new potential request *h* which occurs with probability $p_h(k+\ell)$, $w_j(k+l)$ is the number of stops estimated for vehicle *j* at instant $k+l$. To explain the flexibility of the formulation and economic consistency, the travel time is weighted by a factor $\theta_v$, and the waiting time is weighted by $\theta_e$. Similarly, we will assume a generic expression for the vehicle operation cost, with a component which depends on the total traveled distance, weighted by a factor $c_L$, and another which depends on the total operational time, in this case at unitary cost $c_T$. Thus, $D_i^j(k+\ell)$ represents the distance between stops *i-1* and *i* in the sequence of vehicle *j*. Given the mono-objective nature of this formulation, expression (5) is generalized assuming an arbitrary factor $\lambda$ to be defined by the decision maker.

## 3. HYBRID PREDICTIVE CONTROL BASED ON EVOLUTIONARY MULTIOBJETIVE OPTIMIZATION FOR THE ROUTING PROBLEM

### *3.1 HAPC based on Evolutionary Multiobjetive Optimization (HAPC-EMO).*

The HAPC-EMO strategy is a generalization of HAPC where the optimal control action is selected based on a criterion which takes solutions from the optimal Pareto region considering the following multiobjective problem:

$$\underset{S_k^{k+N}}{Min}\ \{J_1, J_2\} \tag{8}$$

with $J_1$ and $J_2$ corresponding to the defined objective functions in (5). Note that this scheme does not need to define an arbitrary parameter $\lambda$ as stated in (5). The solution of this problem corresponds to a set of control sequences, which form the optimal Pareto set. In this case, as the control sequences are integer and also defined within a feasible finite set, the resulting optimal Pareto front corresponds to a set with a finite number of elements. From the Optimal Pareto front, it is necessary to select only one control sequence $S^i=\{S^i(k),\ldots\ldots,S^i(k+N_u-1)\}$ and from that, apply the control action $S^i(k)$ to the system according to the receding horizon concept. For the selection of this sequence, a criterion related to the importance given to both the user ($J_1$) and operator ($J_2$) costs in the final decision is needed. Note that the solutions obtained from the EMO problem form a set, which includes as a particular case, the optimum obtained from the mono-objective problem defined in Section 2. Figure 3 shows that HAPC solution belongs to the set of possible solutions given by HAPC-EMO.

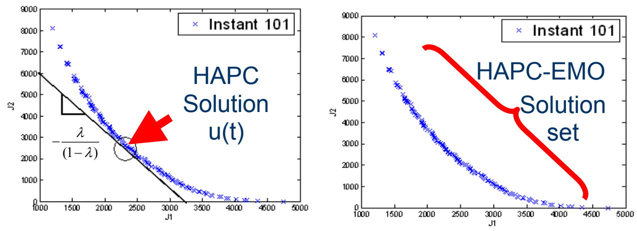


Fig. 3 HAPC solution belongs to EMO-HPC set.

A relevant application of this approach in the controller's dispatching decision is the definition of criteria to select the best control action at each instant under the HAPC-EMO approach. For example, once the best Pareto front is found, different criteria regarding a minimum allowable level of service can be used dynamically to make policy dependent routing decisions. In this work, we will evaluate three criteria of level of service:

*Criterion 1: user cost under Ch$1000 per passenger.*
*Criterion 2: user cost under Ch$1125 per passenger.*
*Criterion 3: user cost under Ch$1250 per passenger.*

Ch$ stands for Chilean pesos. In cases where the policy is accomplished for several solutions, the one that minimizes the operator cost will be selected. If the policy can not be respected (no feasible solution for such a policy exists), the best solution found (the closest to the policy boundaries) is applied. Results and analysis of these operation policies from simulations are reported in Section 4. Next, in Section 3.2, we will explain the multiobjetive optimization method based on Genetic Algorithms (GA) proposed for this problem.

### *3.2 Genetic Algorithms to find Pareto Optimal set.*

Genetic Algorithms (GA) is used to solve the stated EMO problem. In GA, a potential solution is denoted as individual, and it can be represented by a set of parameters. For this application, an individual will represent a feasible control sequence $S^i=\{S^i(k),\ldots,S^i(k+N_u-1)\}$, in which each *gen* or element of the set corresponds to a control action, and the length of the individual is given by the control horizon $N_u$. Using GA, the best adapted individuals will be selected with greater probability to ensure a good offspring. The best parents are then selected and recombined to produce a new generation. For the recombination, two fundamental operators are used: *crossover* and mutation. For the *crossover* mechanism, two portions of genes are interchanged with a certain *crossover* probability. The mutation operator randomly alters each portion of the individual with a certain mutation probability. It is worth to mention that eventually unfeasible individuals can be generated, and these could be eliminated from the population (abortive strategy) or be kept (pro-life) whereas fixing them or penalizing them highly.

At each stage of the algorithm, to find the optimal Pareto set, the best individuals will be those who belong to the best Pareto set found until the current iteration. This, due to the fact that there are solutions which belong to the optimal Pareto region but they have not been found yet, and there are solutions that seem to belong to the optimal Pareto region, but they do not belong because at that stage of the algorithm, the Pareto-dominant solution has not been found.

GA has demonstrated to be an efficient algorithm for this kind of problem (Sáez et al., 2007). The solution using GA in HAPC-EMO gives sub-optimal Pareto fronts, but very close to the global optimum. The most important computational effort of applying this algorithm is in computing the predictions, which are recursively calculated using the model and the control action given by the individual. However, by tuning the number of individuals and number of generations, the computational time can be bounded in order to satisfy a time requirement.

## 4. SIMULATION RESULTS

In this section we summarize the simulation tests conducted to show the HAPC-EMO approach application. A time of two representative hours of a labor day (14:00-14:59, 15:00-15:59) are simulated, over a service urban area of approximately 81 km$^2$. A fleet of four vehicles is considered, with a capacity of four passengers each. We assume that the vehicles travel through a straight line between stops and on a transport network that behaves according to an unknown speed distribution. We also assume that the future calls are unknown for the controller. However, we have historical data from where the speed distribution model and typical trip patterns can be extracted. The speed distribution and the historical data generated by simulation follow the trip patterns (arrows) shown in Figure 4 a) and b) respectively. From the historical data and the fuzzy zoning method proposed in Sáez *et al.* (2007), the pickup and delivery coordinates and probabilities are determined.

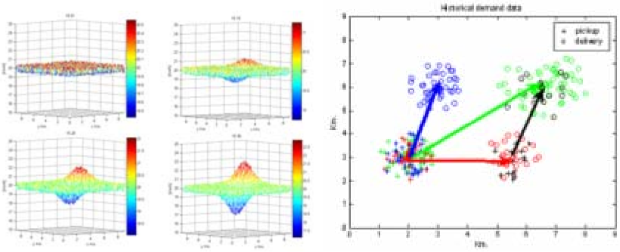

Figure 4. a) Distribution of speed. b) Demand and origin-destiny patterns.

Sixty calls were generated over the simulation period of two hours following the spatial and temporal distribution observed from the historical data. Regarding the temporal dimension, a negative exponential distribution for time intervals between calls with rate 2 [call/minute] for both hours of simulation was assumed. Regarding the spatial distribution, the pick-up and delivery coordinates were randomly generated within each zone. The 10 first calls at the beginning and the 10 last calls at the end of the experiments were deleted from the statistics to avoid boundary distortion (warm up period). 50 replications of each experiment were carried out to obtain the global statistics. Each replication took 20 minutes in average, in a Pentium® D, 2.40Ghz processor. The objective function is formulated at two steps ahead, considering parameters:
$\theta_v$=16,7[\$/min], $\theta_e$ =50[\$/min], $c_T$=25[\$/min], $c_L$=350[\$/Km].

The first set of results were of the HAPC approach with mono-objective functions, computed for weights $\lambda$*=1, 0.75, 0.5, 0.25* and *0*, in order to verify that the objectives pursued by users and operator are effectively opposite. Table 1 shows average values per user or vehicle according to the case, computed from the 50 replications experiment.

In order to analyze and evaluate the performance of the HAPC-EMO strategies, simulations for two steps ahead prediction were performed, under the same conditions. The results of 50 replications with GA using 20 individuals and 20 generations are reported in Table 2, showing the effective user waiting and travel time, and the average travel time and distance associated with vehicles, for the HAPC-EMO, with *N=2* and the three criteria of level of service proposed in Section 3.1.

Table 1: HAPC with different cost functions

| Weight factor $\lambda$ | Travel time [min/pax] | Waiting time [min/pax] | Time travelled [min/veh] | Distance travelled [km/veh] |
|---|---|---|---|---|
| $\lambda = 0$ | 14.0512 | 25.3705 | 82.4936 | 21.8086 |
| $\lambda = 0.25$ | 16.2678 | 12.7871 | 106.2952 | 26.8951 |
| $\lambda = 0.5$ | 16.4896 | 10.4631 | 111.3786 | 27.4946 |
| $\lambda = 0.75$ | 15.8964 | 9.4583 | 113.7029 | 28.6032 |
| $\lambda = 1$ | 16.2400 | 8.4579 | 121.7460 | 30.8408 |

Table 2: EMO HAPC with different criteria

| EMO CRITERIA | Travel Time [min/pax] | Waiting Time [min/pax] | Time travelled [min/veh] | Distance travelled [km/veh] |
|---|---|---|---|---|
| *Criterion 1* | 15.8817 | 14.9941 | 94.4766 | 27.3942 |
| *Criterion 2* | 15.3825 | 16.6497 | 91.7576 | 26.8549 |
| *Criterion 3* | 14.8654 | 18.5962 | 88.5647 | 24.1264 |

Figure 5 shows the global results obtained from both approaches: HAPC and HAPC-EMO, detailing the cost components to global users and operators using the different criteria. Note from Figure 5 that in fact the premise that the objectives (users and operator) are opposite is verified at least in these simulated examples. The HAPC-EMO approach generates a range of non dominated options for the decision maker to decide the operation policy in real time with richer information, not possible to be provided with a traditional HAPC approach. Furthermore, it is possible to add solutions under certain criteria (motivated by user level of service as well as operation savings). In this work three service level criteria were explored. Under criterion 1 we obtained a user cost equal to \$1014.4 similar to the \$1000 constrained by the service policy. Under criterion 2 we obtained a user cost equal to \$1088.86 lower than the \$1125 specified in the service policy. Finally, under criterion 3 we obtained a user cost equal to \$1177.7 which is lower than \$1250 so the service policy is also fulfilled here.

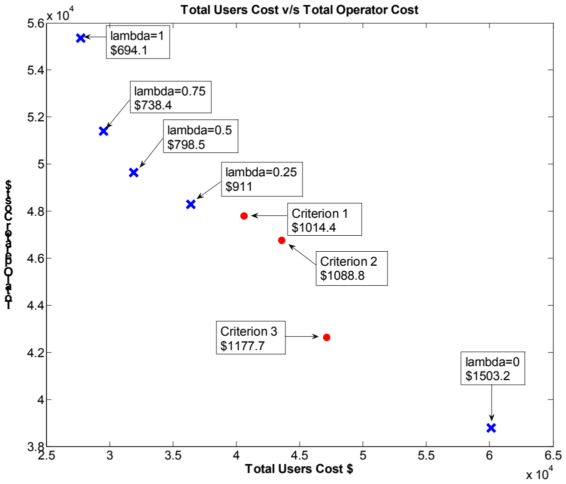


Figure 5. Global statistics. HAPC with different lambda values and solutions with EMO criteria.

## 5. CONCLUSIONS

This work presents a new approach to solve the DPDP under a Hybrid Predictive Control scheme using Evolutionary Multiobjective Optimization. We propose three different criteria to obtain control actions over real-time routing using the dynamic Pareto front. The criteria allowed giving priority to a service policy for users, ensuring a minimization of operational costs under each proposed policy. The service policies are verified approximately in the average of the replications. Priorizing is different to penalizing, and under an implemented on-line system it is easier and transparent for the operator to follow service policies instead of tuning weighting parameters dynamically. The multiobjetive approach allowed to obtain solutions that are directly interpreted as part of the Pareto front instead of results obtained with mono-objective functions, which lack of direct physical interpretation (the weight factors are tuned but they do not allow to apply operational or service policies such as those proposed here). Thus, we searched for more generic solutions. As further research, provided that the most used controllers are not based on EMO, we expect to analyze in detail the relation between EMO and HAPC, to determine weight factors emulating the behavior of EMO. Besides, the sense of applying other service policies will be investigated like adding vehicles, and also different algorithms to solve the DPDP under EMO will be developed and tested.

## ACKNOWLEDGMENTS

This work has been partially financed by projects Anillo ACT-32/2006, by Millenium Institute in Complex Engineering Systems and by FONDECYT projects 1061156, 1061261.

## REFERENCES

Alvarez J. and Cruz C. "Multiobjective dynamic optimization of discrete-time systems", Proceedings of the 37th IEEE Conference on Decision & Control, Tampa, Florida USA. December 1998.

Cortés C. E., Núñez A. and Sáez D. (2007) "Hybrid Adaptive Predictive Control for a Dynamic Pickup and Delivery Problem including Traffic Congestion". Accepted, International *Journal of Adaptive and Signal Processing*.

Desrosiers J., Soumis F., and Dumas Y. (1986). A Dynamic Programming Solution of a Large-Scale Single-Vehicle Dial-a-Ride with Time Windows, *American Journal of Mathematical and Management Sciences* 6, 301-325.

Farina N., Deb K. and Amato P. (2004). Dynamic Multiobjective Optimization Problems: Test Cases, Approximations, and Applications, in *IEEE Transactions on Evolutionary Computation, Vol 8, No 5,* pp. 425.

Desrosiers J., Soumis F., and Dumas Y. (1986). A Dynamic Programming Solution of a Large-Scale Single-Vehicle Dial-a-Ride with Time Windows, *American Journal of Mathematical and Management Sciences* 6, 301-325.

Ichoua S., Gendreau M. and Potvin J. Y. (2005). Exploiting Knowledge about Future Demands for Real-Time Vehicle Dispatching, aceptado para publicación en *Transportation Science*.

Kerrigan E.C., Bemporad, A., Mignone, D., Morari, M. and Maciejowski, J.M. (2000). "Multi-objective Priorisation and Reconfiguration for the Control of Constrained Hybrid Systems". Proceedings of the American Control Conference, Chicago Illinois, June 2000. Page 1694-1698.

Kerrigan E.C. and Maciejowski J.M., (2003) "Designing model predictive controllers with prioritised constraints and objectives," Proceedings. 2002 IEEE International Symposium on Computer Aided Control System Design, 18-20 Sept, pp. 33 – 38.

Laabidi K. and Bouani F. (2004) "Genetic Algorithms for Multiobjective Predictive Control", Proceedings of the 2004 IEEE International Symposium on Control, Communications and Signal Processing, pp 149-152.

Sáez D., Cortés C. E. and Núñez A. (2007), "Hybrid adaptive predictive control for the multi-vehicle dynamic pick-up and delivery problem based on genetic algorithms and fuzzy clustering", Computers & Operations Research, In Press. http://dx.doi.org/10.1016/j.cor.2007.01.025.

Savelsbergh M. and Sol M. (1995). The general Pickup and Delivery problem, *Transportation Science,* Vol. 29, No. 1, pp. 17-29.

Subbu R., P. Bonissone, N. Eklund, Y. Weizhong, N. Iyer, X. Feng, S. Rasik, (2006) "Management of Complex Dynamic Systems based on Model-Predictive Multi-objective Optimization," Computational Intelligence for Measurement Systems and Applications, Proceedings of 2006 IEEE International Conference, July, pp. 64 – 69.

Tan K.C, Cheong C.Y. and Goh C.K. (2007). Solving multiobjective vehicle routing problem with demand via evolutionary computation. *European Journal of operational research* 177, pp. 813-839.

Topaloglu H. and Powell W. (2005). A Distributed Decision-Making Structure for Dynamic Resource Allocation Using Non Linear Functional Approximations, *Operations Research* 53(2), 281-297.