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A Multi-objective Evolutionary scheme for Control Points deployment in Intelligent Transportation Systems

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ABSTRACT

One of the problems that hinder emergency in developing countries is the problem of monitoring activities through inter-urban roadway networks. In the literature, the use of control points is proposed in the context of these countries in order to ensure efficient monitoring, by ensuring a good coverage while minimizing the installation costs as well as the number of accidents across these road networks. In this work, we propose an optimal deployment of these control points from several optimization methods based on some evolutionary multi-objective algorithms including the Non dominated Sorting Genetic Algorithm-II (NSGA-II), the Multi-Objective Particle Swarm Optimization (MOPSO), the Strength Pareto Evolutionary Algorithm -II (SPEA-II), and the Pareto Envelope based Selection Algorithm-II (PESA-II). We performed the tests and compared these deployments using Pareto front and performance indicators like the Inverted Generational Distance (IGD), Spread and Hypervolume. The results obtained show that the NSGA-II method is the most suitable for the deployment of these control points.

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1. INTRODUCTION

Today, monitoring activities through road transport networks remain a serious problem for both developed and developing countries since road accidents cause huge losses. Shoukrallah and Rifaat [1] noted that around the world, we have about 1.2 million people killed on the road in 2008 at an estimated total cost of $ 518 billion, and 50 million people are injured in road accident. Moreover Jadaan Khair et al [2] in their work on a comparative analysis of road safety in developed and developing countries showed that 90% of deadly accidents are caused in developing countries while these countries only have 54% of the global vehicle rate. The emergence of Intelligent Transportation Systems (ITS) together with the new generation of mobile networks contribute to a serious reduction of the death rate on the roads [3, 4]. These systems exploit technological advances of telecommunications to facilitate communication among users, precisely monitor activities in road network [5]. It would be very interesting for such a concept to be implemented in developing countries especially in the context of road networks. Despite the limited financial means available in such countries for setting up such projects.

In the case of the developing countries, more work are aimed at laying the groundwork for road networks oversight models for inter-urban transport. For instance, based on some factors such as city-wide traffic management and monitoring, smart parking and public transportation information services, Gohar et al. [6], proposed a big data analytics architecture for ITS. Moreover, Silva et al. [7] studied smart cities in the context of ITS while reviewing their features and characteristics as well as some challenges and opportunities. Furthermore, sustainable smart city schemes and framework have been developed in order to enhance ITS users mobility in some cities of developing countries [8, 9]. However, these models should consider the infrastructural realities of these countries.

Thus, Mfenjou et al [4] proposed a methodology that aims at contextualizing an ITS by taking into account the infrastructural realities. In [10], the authors proposed a monitoring communication architecture for developing countries' inter-urban road networks based on control points. They then introduced a deployment model for these control points according to the following criteria: minimizing the installation cost of these points, maximizing network coverage and considering areas where accidents are frequently occurring through an inter-urban road network in developing countries. This deployment was performed using the Non-Dominated Sorting Genetic Algorithm II (NSGA-II). For the experimented scenarios, authors end up at the Pareto front, which offers the opportunity for decision-makers to take decisions according to its priorities.

Several works focus on the issues of regulation and monitoring of activities in the transport systems of developing countries. For the reduction of traffic violation such as speed violation, Tarapiah et al. [11] propose a smart on-board transportation management system using GPS/GPRS. This on-board GPS/GPRS system can be attached to vehicle. This system can help to track a vehicle depending on their position using Google map. This system offers innovations in terms of vehicle tracking in developing countries. No information is sent between the decision-making and the road users in relation to the dissemination of information on road traffic.

Moreover, the proposed works in [12] offer an automatic survey system for paved and unpaved road classification and road anomaly detection using smartphone sensor. This solution can only be used to detect obstacles across the road transport network. It may have an impact incidents that occur on the roads, but without communicating obstacles to other users. On the another hand, Patel et al [13], propose a survey on ITS using the Internet of Things (IoT). It presents the advantages and disadvantages of proposed approaches in the use of the IoT for ITS. However, technologies used on the IoT could be exploited for the regulation or monitoring of activities through inter-urban road networks in developing countries. Likewise, the work of Mfenjou et al [10] focuses on monitoring activities through an inter-urban road network by setting up a communication architecture based on control points in order to improve the regulation of inter-urban road networks in developing countries. The proposed deployment was done using an optimization method: NSGA-II. It would be interesting to use several optimization methods to see which one could give better solutions. The following section provides a literature review of some optimization methods.

The purpose of this work is to perform the deployment of the control points using some optimization methods including the Non dominated Sorting Genetic Algorithm-II (NSGA-II), the Multi-Objective Particle Swarm Optimization (MOPSO), the Strength Pareto Evolutionary Algorithm -II (SPEA-II), and the Pareto Envelope based Selection Algorithm-II (PESA-II). Indeed, the use of several optimization method's leads to an evaluation of it thanks to the performance indicators. For comparison purpose, among the considerable number of performance indicators available in the literature, we adopted the Inverted Generational Distance (IGD), Spread and Hypervolume.

The rest of the paper is organized as follows : In Section 2., we review some optimization methods based on evolutionary algorithms and their applications in the context of nodes or control points deployment. As for section 3., we propose a methodology to be adopted to carry out the deployments of the controls points and to analyze the obtained results. Concerning the section 4., we present the results of the Pareto front of the non dominated solutions resulting from the used methods of optimization. Then, we evaluate these optimization methods thanks to some performance indicators. Finally, section 5. summarizes, concludes and introduce the future work.

2. OVERVIEW OF SOME OPTIMIZATION METHODS
2.1. Multi-Objective Genetics Algorithms

Introduced by John Holland [14], Genetics Algorithms are one of the most used evolutionary algorithms. Whether in the context of single-objective problems or multi-objective problems, they are based on:

- Encoding [15]: It is at this step that we define how we want to represent the information that we must process. The coding can then be binary, octal, hexadecimal, real, permutation and tree encoding.
- Selection [16, 17]: At this level of Genetic Algorithm, it finds out the best individuals for mating process so that the offsprings produced are better than the previous population. Depending on how the best individual is sought, several methods of selection exist, but the most known are: the roulette wheel selection, the linear rank selection, the exponential rank selection, the tournament, the truncation selection.
- Crossover [18, 19]: Here, the operation consists to merge two parents to generate a third new individual. There are also many variants of crossover: single point crossover, N point crossover, uniform crossover, three parent crossover, arithmetic crossover.
- Mutation [20, 21]: Here, the algorithm must generate solutions that are overall likely solutions. We also have several types of mutations: insert mutation, inversion mutation, scramble mutation, swap mutation, flip mutation, interchanging mutation, reversing mutation, uniform mutation, creep mutation.
- Evaluation [14]: The objective function is used here to check whether the individual (if he optimizes function). Otherwise, we go back to the selection.
- Replacement [22, 23, 20]: In addition to an individual to be the best, it would reflect the related problem initially posed in the reality. There are many types of replacement: generational replacement, steady state replacement, elitism, delete n-last, delete n, weak parent replacement, both parents replacement, random replacement.

We are interested in problem solving by multi-objective algorithms. They are grouped into three classes [24]:

- *Aggregating function*. The goal of aggregating functions is to turn a multi-objective problem into a single goal problem through an equivalent objective function. it exists under several types but the best known is the
- weighted average. It combines all the objective functions into one on the forms given in Eq. 1.

  $$min \sum_{i=1}^{n} w_i f_i(x) \quad where \;\; w_i \geq 0 \, and \, \sum_{i=1}^{n} w_i = 1. \tag{1}$$

  where $w_i \geq 0$ are the weighting coefficients. Their values are given according to the importance of the objective function with which it is associated.
- *Population-based approaches*. This approach uses subpopulations to optimize each goal independently. Here, the research is diversify thanks to the population and the notion of Pareto is not directly taken into account in the selection process. The most known of this method is VEGA (Vector Evaluated Genetic Algorithm). The particularity of VEGA is in the way of selecting. A sub-population is generated at each generation from the initial population for each objective. For k objectives, k sub-populations of $\frac{p}{k}$ individuals are generated (p is the number of individuals in the initial population). These sub-populations are then gathered together to obtain a new population on which the genetic operators will be applied
- *Pareto-based approaches*. The objective is to use Goldberg's [25] Pareto-Dominance for solving the problems introduced by [26]. The idea is to use the concept of optimality to respect all the criteria without comparing the values of different criteria. Let E be a set of possible multi-objective solutions. A point x is Pareto-optimal if it is not dominated by any point belonging to E. x belongs to the set of non-dominated solutions. This approach is grouped into two methods: the elitist method and the non-elitist method. The non-elitist method do not preserve the "Pareto-optimal" individuals found over time.

They hardly maintain the diversity on the Pareto border. Finally, the convergence of solutions towards the Pareto border is generally slow [27].

Concerning the elitist method, the algorithms used in this approach solve the shortcomings found in non-elitist methods by introducing an external population or archive to keep Pareto-optimal individuals, the preference for non-dominated solutions and the use of efficient distribution of solutions on the Pareto borders. Being more interesting and more advantageous than non-elitist methods, we chose to work with some elitist methods namely: NSGA-II (Nondominated Sorting Genetic Algorithm II), SPEA-II (Strength Pareto Evolutionary Algorithm -II), PESA-II (Pareto Envelope based Selection Algorithm-II).

2.1.1. NSGA-II (Nondominated Sorting Genetic Algorithm II)

This is one of the most used optimization methods. Its efficiency is recognized since compared to some optimization methods its complexity is O(mN^2). It is based on a classification of individuals in several levels [28]:

- It uses the elitist approach that gives it the ability to save the best solutions found from previous generations.
- It uses a calculation function of the crowding distance. This calculation makes it possible to choose the best solutions in a Pareto front. This ensures a uniform dispersion of solutions on the Pareto front.

2.1.2. SPEA-II (Strength Pareto Evolutionary Algorithm II)

This is an evolutionary multi-objective algorithm wich are [29]:

- An improved fitness assignment scheme is used, which takes for each individual into account how many individuals it dominates and it is dominated by.
- A nearest neighbor density estimation technique is incorporated which allows a more precise guidance of the search process.
- A new archive truncation methods guarantees the preservation of boundary solutions.

2.1.3. PESA-II (Pareto Envolope based Selection Algorithm II)

It is also another optimization method based on evolutionary multi-objective algorithms. It uses a better technique for selecting individuals. Here, instead of assigning, a selective fitness to an individual, selective fitness is assigned to the hyperboxes in which space is currently occupied by individuals in the current approximation to the Pareto frontier [30]. This method is more sensitive to ensuring a better spread along the Pareto frontier than individual based selection.

2.2. Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is developed by Kennedy and Eberthart [31]. The swarm of particles are possible solutions, optimization consists of browsing the search space to find the global optimum. [32] present the global version of PSO. Every particle of the swarm keeps tracks of its coordinates in the problem space which are associated with the best solution it has achieved. This solution is called *pbest*. The best solution value of all the swarm particle is called *gbest*. The aims of PSO is therefore to improve the *gbest* value. In fact, its consists of; at each time step, updating the velocity each particle toward its *pbest* and *gbest* locations. This algorithm is based on the social behavior of animals that evolve swarm like schools of fish and flights of birds groups. It is a dynamic that springs from the local information, rules and memory of each individual that forms the basis of their movement while maintaining cohesion with the rest of the animals in the group. From this information and rules, we quote: ”stay close to the other individual”, ”go in the same direction” , ”go at the same speed as the others”. The movement of a particle is therefore influenced by the component of inertia, the cognitive component and the social component. Concerning the component of inertia, the particle tends to follow the current direction. About the cognitive component, a particle tends to move towards the best site by which it has already passed. Finally, as for the social component, a particle tends to rely on the experience of its neighbors. The swarm is then composed of a set of particles each of which has a position (solution vector) and a speed. Any particle also has a memory allowing him to remember his best performance and that of his neighbors. The swarm of particles are possible solutions, optimization consists of

Algorithm 1: Particle Swarm Optimization

Begin

1. ***Initialization Phase:*** Randomly N particles with their positions and velocities on d dimensions in the problem space
2. ***Evaluation***: For each particle, evaluate the desired optimization fitness function in d variables
3. ***Comparison of Particle's fitness evaluation with particle's pbest***
   If current value is better than *pbest* ***then***
   set *pbest* value equal to the current value;
   the *pbest* location equal to the current location in d-dimensional space;
4. ***Compare fitness evaluation with the population's overall previous best***
   If current value is better than *gbest* ***then***
   reset *gbest* to the current particle's array index and value;
5. ***Change the velocity and position of the particle according to Eq. 2 and Eq. 3 respectively***

$$v_{id} = v_{id} + c_1 * rand() * (p_{id} - x_{id}) + c_2 * Rand() * (p_{gd} - x_{id}) \tag{2}$$

$$x_{id} = x_{id} + v_{id} \tag{3}$$

6.***Loop step 2***: Until a criterion is met, usually a sufficiently good fitness or a maximum number of iterations (generations);

7.**End.**

browsing the search space to find the global optimum. Eberhart and Shi [32] illustrate the process of the global version of PSO that we summarize as follows in Algorithm 1.

The main variables of this algorithm are:

1. v_{id} is the velocity of particle i in dimension d. $d \in [1, D]$
2. *rand()* and *Rand()* are the function that generate randomly two number in [0,1] at any iteration to control respectively cognitive and social components.
3. p_{id} is the best solution of particle i in dimension d
4. p_{gd} is the best global dimension d
5. x_{id} is the vector of position of particle i in dimension d
6. c_1 and c_2 are two constants that represents the coefficients of velocity respectively for the control of the cognitive component and social component. Its represent the weighting of the stochastic acceleration terms that pull each particle toward *pbest* and *gbest*. Low particles to roam far from target regions before being tugged back, while high values result in abrupt movement toward, or past, target regions.

PSO has been improved either by the modification of certain parameters, have the confinement of particles [33], the constriction factor [34], the inertia weight [35], the neighborhood topology [31]. Among the improved versions, we have FIPS (Fully Informed Particle Swarm) [36], 5TRIBES algorithm [37], PSO and hybridization [38, 39, 40] and Cooperative PSO [41].

For instance, the Multi-Objective Particle Swarm Optimization is an extending methodology of the Particle Swarm Optimization problems. This approach uses the concept of Pareto dominance to determine the flight direction of a particle and it maintains previously found Non-dominated vectors in a global repository that is later used by other particles to guide their own flight [42]. The work of Alvarez-Benitez et al. [43] presents the multi-objective behavior of this optimization method. For finding the best way of selecting the guides for each particle in the swarm, they propose an archive which contains the Non-dominated solutions found by the algorithm so far.

Hence, this section allowed us to review the optimization methods that we used in the rest of this work. The following section proposes the approach we consider for the evaluation of the deployment of control points.

3. OUR PROPOSED SCHEME

3.1. Problem formulation and design goal

The architecture presented in Fig. 1 adapts to the technological and infrastructural context of these countries. It is based on control points. Two types have been defined: the Treatment Control Points (TrCP) and the Relay Control Points (RCP). The Treatment Control Point (TrCP) are defined to process the information collected by Relay Control Point. The information concern the behavior of vehicles traveling and disturbances through the inter-urban transport network in developing countries.

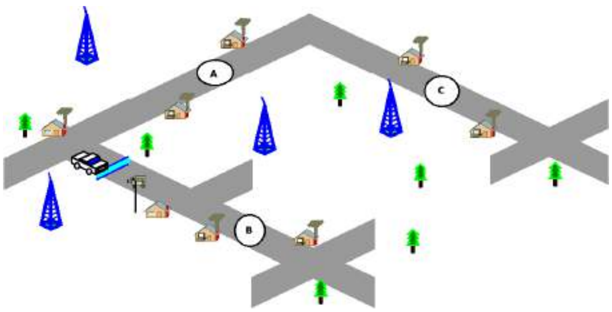


Figure 1. Communication architecture of Control Points.

According to the deployment of these control points, their implementation is based on two objectives: to minimize installation costs and to maximize the coverage of the inter-urban road network. The multi-objective formulation given in Eq. 8 associated with this type of control point according the objectives F_1 and Z_1 (see Eq. 4 and Eq. 5) as well as constraints C_1 and C_2 given in Eq. 6 and Eq. 7.

- F_1: the objective function which represents the cost of deployment of TrCPS.

$$F_1 = \sum_{i \in N \subseteq \mathbb{N}} \sum_{j \in S \subseteq E} c_{i,j} x_{i,j} \tag{4}$$

- Z_1: it allows us to maximize the coverage of the inter-urban roadway network. In fact, Z_1 guarantees that whatever position is chosen, all vehicles passing through the road network will be visible and registered by at least one TrCP.

$$Z_1 = \sum_{i \in N \subseteq \mathbb{N}} \sum_{j \in S \subseteq E} \sum_{\substack{k \\ k,l \notin S}, l \in E} m_{k,j} m_{j,l} x_{i,j} \tag{5}$$

where $m_{i,j}$ is a boolean variable which is equal to 1 if there is an edge starting from i to j and 0 otherwise.

The corresponding constraints C_1 and C_2 are given in Eq. 6 and Eq. 7.

$$C_1 : \sum_{i \in N \subseteq \mathbb{N}} x_{i,j} \leq n_1^*, \forall j \in S \subseteq E \tag{6}$$

$$C_2 : \sum_{i \in N \subseteq \mathbb{N}} \sum_{j \in S \subseteq E} x_{i,j} \leq n_2^*, \; x_{i,j} \in \{0,1\}, \forall i \in N, \forall j \in S \subseteq E \tag{7}$$

Table 1. Notations

Variable	Notation
Deployment cost to build at location j $TrCP_i$	$c_{i,j} > 0$
Decision variable to open or not the $TrCP_i$ at location j	$x_{i,j} \in \{0,1\}$
The number of TrCPs candidates	N
The set of admissible TrCP positions	$S \subseteq E$
Thresholds limiting the number of TrCPs	$n_2^* \in \mathbb{N} \cup \{+\infty\}$
The number of TrCP at a given location	$n_1^* \in \mathbb{N} \cup \{+\infty\}$

$$\begin{cases} \text{Minimize } F_1 \\ \text{Maximize } Z_1 \\ \text{subject to } C_1 \text{ and } C_2 \end{cases} \tag{8}$$

The notations used for modeling the optimization problem of TrCPs is given in Tab. 1.

Furthermore, according to the RCPs that used to collect information through the inter-urban road network, their deployment are done by ensuring a coverage of the network, minimizing the cost of installation and give the priority to areas where accidents are mostly caused by user. As result, the multi-objective reformulation given in Eq. 15 is then based on three functions F_2, Z_2 and Z_3 (see Eq. 9, Eq. 10 and Eq. 11) as well as constraints C_3, C_4 and C_5 (see Eq. 12, Eq. 13 and Eq. 14).

Now, let us define $m_{u,v}$ as a boolean variable which is equal to 1 if there is an edge starting from u to v and 0 otherwise; $\overline{m}_{u,v}$ as a boolean variable which is equal to 1 if there is a way starting from u to v and 0 otherwise; and $a_{u,v}$ that denotes the number of accidents registered on an existing edge starting from u to v (it can be generalized to a function of the number of accidents).

- F_2 the objective function which represents the cost of deployment of TrCPs;

$$F_2 = \sum_{u \in P \subseteq \mathbb{N}} \sum_{v \in Q \subseteq E} b_{u,v} y_{u,v} \tag{9}$$

- Z_2 allows us to prioritize the RCPs around which most accidents occur in a given section;

$$Z_2 = \sum_{u \in P \subseteq \mathbb{N}} \sum_{v \in Q \subseteq E} \sum_{k,l \in E} m_{k,v} m_{v,l} a_{u,v} y_{u,v} \tag{10}$$

- Z_3 guarantees that whatever position is chosen, all vehicles passing through the road network will be visible and registered by at least one RCP;

$$Z_3 = \sum_{u \in P \subseteq \mathbb{N}} \sum_{v \in Q \subseteq E} \sum_{k,l \in S} \overline{m}_{k,v}\ \overline{m}_{v,l} y_{u,v} \tag{11}$$

The constraints C_3, C_4 and C_5 of the optimization problem are derived in Eq. 12, Eq. 13 and Eq. 14.

$$C_3: \quad \sum_{u \in P} \sum_{v \in Q} \overline{m}_{k,v}\ \overline{m}_{v,l} y_{u,v} \geq min\Big\{1,\ \sum_{u \in P} x_{u,k} \sum_{u \in P} x_{u,l} \sum_{v \in Q} \overline{m}_{k,v}\ \overline{m}_{v,l}\Big\},\ \forall k,l \in S \tag{12}$$

$$C_4: \quad \sum_{u \in P} y_{u,v} \leq n_3^*,\ \forall v \in Q \tag{13}$$

$$C_5: \quad \sum_{u \in P} \sum_{v \in Q} y_{u,v} \leq n_4^*,\ \forall y_{u,v} \in \{0,1\}, \forall u \in P, \forall v \in Q \tag{14}$$

$$\begin{cases} \text{Minimize } F_2 \\ \text{Maximize } Z_2 \\ \text{Maximize } Z_3 \\ \text{subject to } C_3,\ C_4 \text{ and } C_5 \end{cases} \tag{15}$$

Table 2. Notations used for modeling the optimization problem of RCPs [10]

Variable	Notation
Deployment cost to build RCP_u at location v	$b_{u,v} > 0$
Decision variable to open or not the RCP_u at location v	$y_{u,v} \in \{0, 1\}$
The number of RCPs candidates	P
The set of admissible RCPs positions	$Q \subseteq E$
Thresholds limiting the number of RCPs	$n_3^*, n_4^* \in \mathbb{N} \cup \{+\infty\}$
The number of RCP at a given location	$n_3^* \in \mathbb{N} \cup \{+\infty\}$
The number of registered accidents from u to v	$a_{u,v} \in \mathbb{N}$

Tab. 2 defines the notations used for modeling the optimization problem given in Eq. 15.

Concerning the design Figure 2 illustrates the adopted approach to choose one (or more) method(s) according to the evaluation criteria we chose. For each selected scenario, as basic input parameters, we use:

- *An adjacency matrix*: Consider M the adjacency matrix, $M_{i,j}$ designates the possibility of installing a type *i* control point, at position *j*. It corresponds to the variable m on equations (8) and (15).

- *A cost matrix of installation of Control Point*: This is the cost matrix for deploying control point to admissible positions based on their types.

- *An accident matrix as input parameters*: It defines the number of accidents that occur between the permissible positions of the relay control points (RCP). Thus, $a_{u,v}$ is the number of accidents that occur between point u and point v.

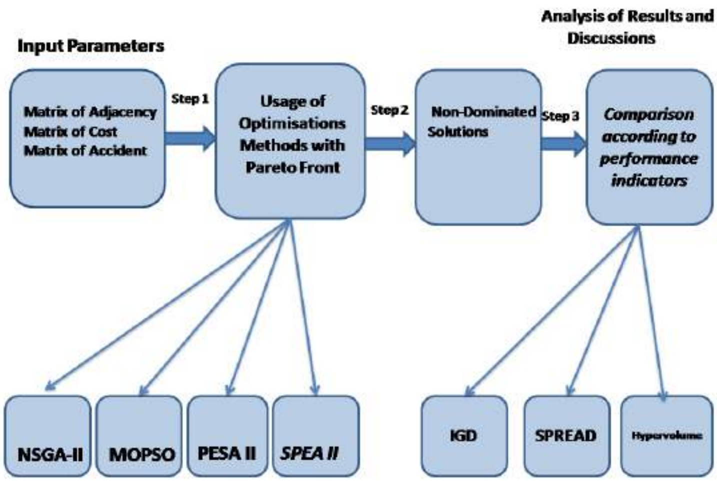


Figure 2. Our Proposal Design

Then we use the previously defined methods that will lead to the development of the Pareto front. The Pareto front allows to highlight for each method, non-dominated solutions. Finally, the chosen performance indicators offer the user the opportunity to select a method in relation to their priorities.

3.2. Framework

Here the binary encoding has been used. Indeed, the objective here is to find the best positions according to the different types of control points. This is in order to minimize the costs of installations by maximizing the coverage of the areas to be monitored and to favor areas with a high accident rate (case of relay points). Thus, for each chosen scenario, we have an $M \times N$ matrix where M represents the number of control point types and N represents the number of possible positions. The other optimization parameters are given in Tab. 3.

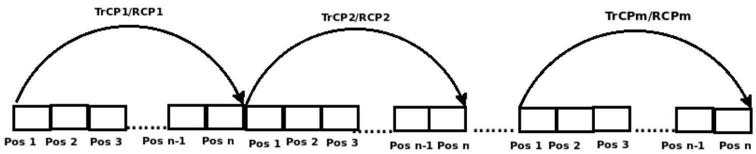


Figure 3. Encoding of TrCPs and RCPs

Table 3. The used parameters of the other optimization methods

NSGA II, PESA II, SPEA II: Common parameters
- *Encoding: Binary encoding*;
- *Selection: Roulette Wheel Selection*;
- *Mutation: Gaussian Mutation*;
- *Crossover: N point crossover, N=2* ;
- *Population size:* 100 ;
- *Number of iterations:* 100;
- *Probability of crossover*=0.7, *Probability of Mutation*=0.4;
- *Number of Mutants=round*(*number of population * Probability of Mutation*);
- *Mutation Rate*= 0.02;

NSGA II: Specifics parameters
Function: Calculation of crowding distance;

PESA II: Specifics parameters
- *Archive size*= 100
- *Grid Inflation*= 0.1
- *Number of Grids per Dimension*= 7.

SPEA II: Specifics parameters
- *Archive size*= 100.

MOPSO: Parameters
Number of itrations= 100; Population size =100;
Repository size= 100; Number of Grids=7;
Personal learning coefficient $C_1 = 1$*; Global learning coefficient* $C_2 = 2$*;*
Inflation Rate=0.1; Leader Selection Pressure= 2; Deletion Selection Pressure=2;

4. PERFORMANCE EVALUATION

In this section, we present the different results of the deployments of both types of control points. It is for all optimization methods. Then, we present the performance evaluation following the selected criteria. Before we get there, the used experimental values are given in Tab 4. The experiments have been done with Matlab in three scenarios including: five, ten and fifteen admissible positions.

Given the obtained curves, it would be important to use the tools for evaluating the performance of optimization methods. The evaluation criteria then allow the user to have a logical orientation on the choice to be made. Certainly, there are several performance metrics. The last make it possible to evaluate and compare the quality of the Pareto front of the multi-objective optimization methods. The work in [44] identified 54 metrics. In addition, according to Okabe et al [45], these metrics take into account three aspects of the solution set including:

- The number of solution;
- The diversify: It is the distribution as well as spread;
- The convergence: This is the closeness of the theoretical Pareto Optimal front.

Among these performance indicators, we choose the spread, the Inverted Generational Distance and the Hypervolume.

1. *Spread.* According to [46] as well as [47], the spread is the metric that gives us a good evaluations results of the approximation. In fact, the spread uses the minimum distance between two successive solutions to the assessment of the distribution of the solution on a given search space. About the comparison of many

Table 4. Input Parameters

- *The matrix of cost is c = random([15 75], NbrTypCapt, Nbrpos);*
- *The matrix of adjacency has been set for each scenario;*
- *The matrix of accident a = random([0 25], Nbrpos, Nbrpos) with modifications like* $a_{i,j} = a_{j,i}$
- *NbrTypCapt is the number of types of control point and Nbrpos represents the number of eligible control points for a given scenario. In this case, NbrTypCapt=03, Nbrpos=05, 10 and 15 (admissible positions).*

Table 5. IGD about TrCPs

Numbers of TrCPs	NSGA-II		MOPSO		PESA-II		SPEA-II	
	Avg	**Stdev**	**Avg**	**Stdev**	**Avg**	**Stdev**	**Avg**	**Stdev**
05	6.67e-01	4.91e-01	1.13e+00	8.10e-01	**4.93e-01**	**4.31e-01**	6.11e-01	4.46e-01
10	1.35e+00	8.38e-01	4.66e+00	3.49e+00	**7.38e-01**	**6.27e-01**	7.54e-01	7.79e-01
15	2.54e+00	1.92e00	3.84e+00	2.03e+00	6.65e-01	4.76e-01	**5.21e-01**	**5.05e-01**

Table 6. Spread about TrCPs

Numbers of TrCPs	NSGA-II		MOPSO		PESA-II		SPEA-II	
	Avg	**Stdev**	**Avg**	**Stdev**	**Avg**	**Stdev**	**Avg**	**Stdev**
05	1.22e+02	1.43e+01	8.96e+01	1.13e+01	**5.76e-01**	**5.76e+00**	2.61e+00	1.68e+00
10	2.42e+02	4.36e+01	2.07e+02	8.37e+01	**1.09e+00**	**1.09e+00**	2.15e+00	1.69e+00
15	3.08e+02	7.80e+01	1.39e+02	8.68e+01	**1.27e+00**	**1.27e+01**	2.90e+00	1.62e+00

Multi-Objective Evolutionary Algorithms, the lowest value of spread is associated to the best algorithm. Its formula is given in Eq. 16.

$$\begin{cases} S = \sqrt{\frac{1}{|P|}\sum_{i=1}^{|P|}(D_i - \overline{D})^2} \\ where \\ \overline{D}\ is\ the\ mean\ of\ D_i \\ D_i = \min_{j\in P\wedge i\neq j}(\sum_{k=1}^{l}|f_k(\overrightarrow{x_i}) - f_k(\overrightarrow{x_j})|). \\ P\ is\ the\ set\ of\ the\ Pareto\ Solution. \end{cases} \tag{16}$$

2. *IGD (Inverted Generational Distance)*. It is used to measure the proximity between the evaluated solutions and the Optimal Pareto front P^* [48]. Among many Multi-Objective Evolutionary Algorithms, the best algorithm is the one which has the lowest value of IGD. It is defined as given in Eq. 17.

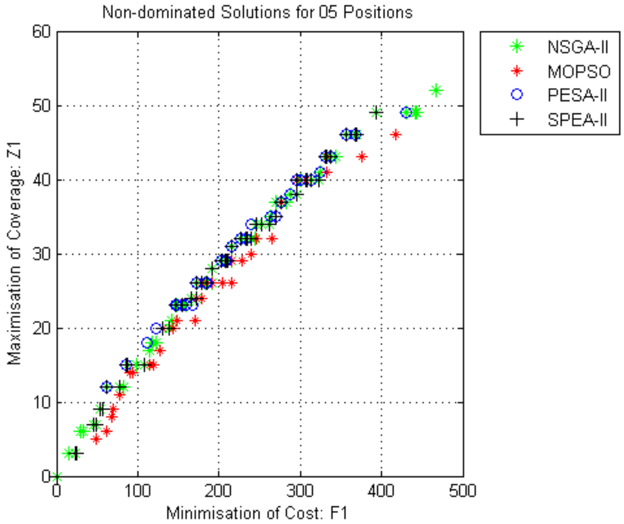
$$\begin{cases} IGD = \frac{(\sum_{i=1}^{|P*|} d_l^*(\overrightarrow{x_l*}))^{\frac{1}{l}}}{|P^*|} \\ where \\ d_l^*(\overrightarrow{x_i}) = \min_{j=1}^{|P|}\sqrt{\sum_{k=1}^{l}(f_k(\overrightarrow{x_i^*}) - f_k(\overrightarrow{x_j^*}))^2} \\ and \\ \overrightarrow{x_i}\ and\ \overrightarrow{x_j}\ are\ solutions\ that\ belong\ respectively \\ \ to\ P^*\ and\ P \end{cases} \tag{17}$$

3. *Hypervolume*: It calculate the volume covered by the solutions in a given objective space. It measures both the diversity and convergence (see Eq. 18). A bigger hypervolume indicator define a better algorithm.

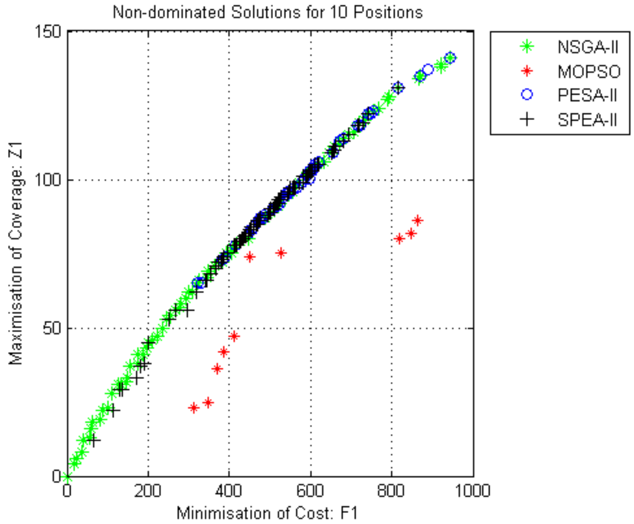
$$HV = volume(\cup_{i=1}^{|P|} V_i) \tag{18}$$

The curves obtained from the optimization methods previously mentioned namely: NSGA-II, PESA-II, SPEA-II and MOPSO. Moreover, the previously mentioned scenarios used namely: five eligible positions, ten eligible positions and fifteen eligible positions. Fig. 4a, Fig. 4b, and Fig. 4c shows the obtained Pareto fronts results for TrCP. Furthermore, Fig. 5a, Fig. 5b, Fig. 5c, and Fig. 5d shows the Pareto fronts results of the RCP with 05 admissible positions. Fig. 6a, Fig. 6b, Fig. 6c, and Fig. 6d shows the Pareto fronts results of the RCP with 10 admissible positions. Fig. 7a, Fig. 7b, Fig. 7c, and Fig. 7d shows the Pareto fronts results of the RCP with 15 admissible positions.

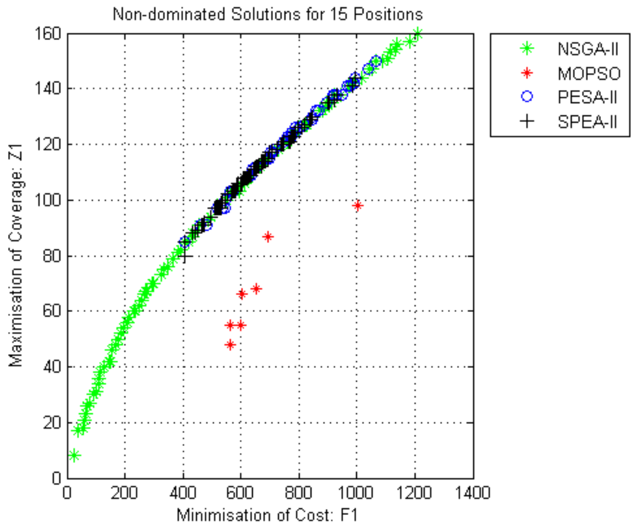
Tab. 5, Tab. 6, and Tab. 7 present the IGD, Spread, and Hypervolume evaluations respectively of the optimization methods applied to the deployment scenarios of TrCP. Concerning the RCP, the IGD, Spread and Hypervolume are shown in Tab. 8, Tab. 9, and Tab. 10, respectively. With respect to the TrCPs, the comparison



(a) 05 positions



(b) 10 positions

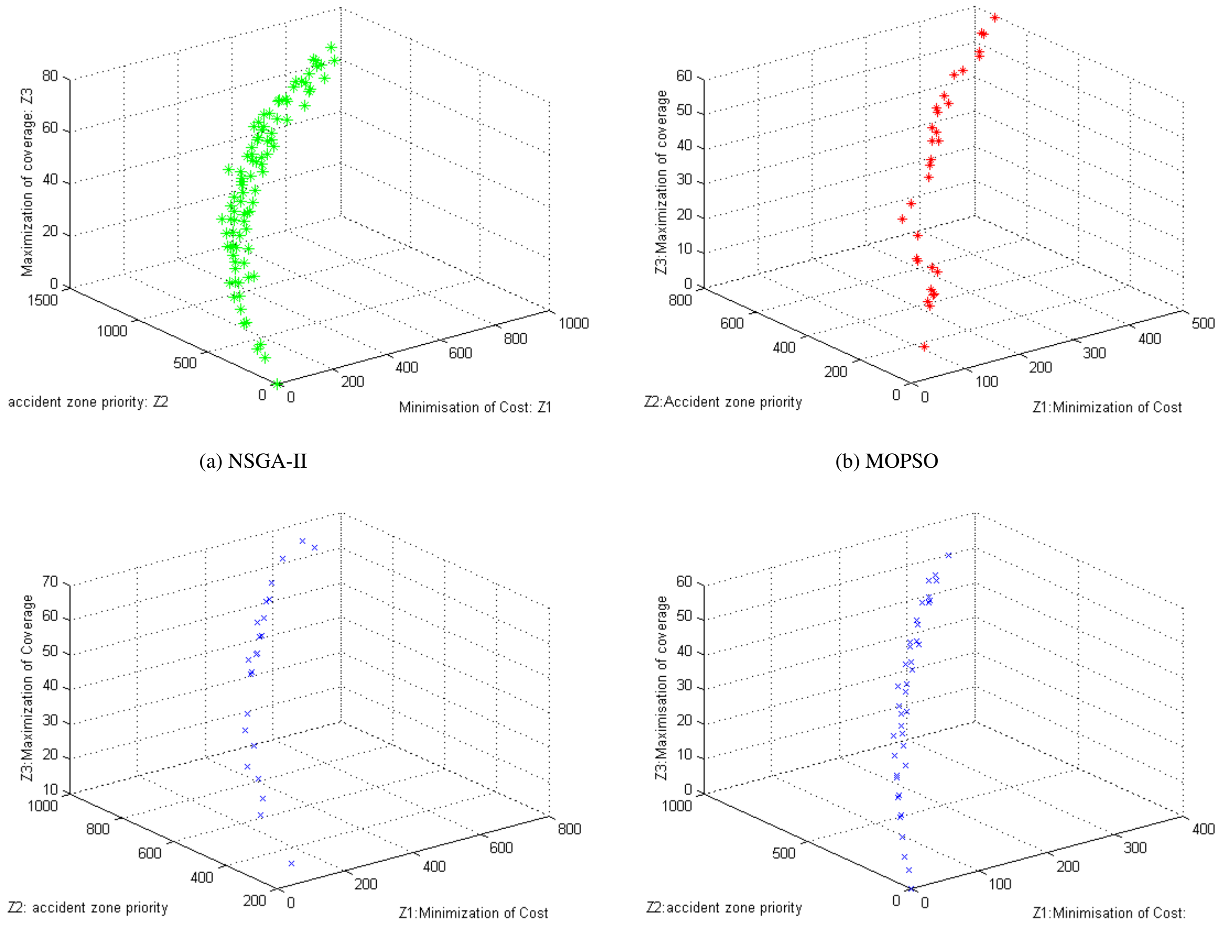


(c) 15 positons

Figure 4. TrCP pareto's front

Table 7. Hypervolume about TrCPs

Numbers of TrCPs	NSGA-II		MOPSO		PESA-II		SPEA-II	
	Avg	**Stdev**	**Avg**	**Stdev**	**Avg**	**Stdev**	**Avg**	**Stdev**
05	**1.55e+04**	**2.66e+03**	8.32e+03	2.54e+03	1.18e+04	2.35e+03	1.15e+04	1.75e+03
10	**6.93e+04**	**1.29e+04**	2.14e+04	1.24e+04	3.75e+04	9.56e+03	5.57e+04	1.17e+04
15	**9.92e+04**	**3.52e+04**	9.23e+03	7.91e+03	2.84e+04	8.10e+03	3.55e+04	2.11e+04



(a) NSGA-II (b) MOPSO

(c) PESA-2 (d) SPEA-2

Figure 5. RCP pareto's front with 05 admissible positions

Table 8. IGD about RCPs

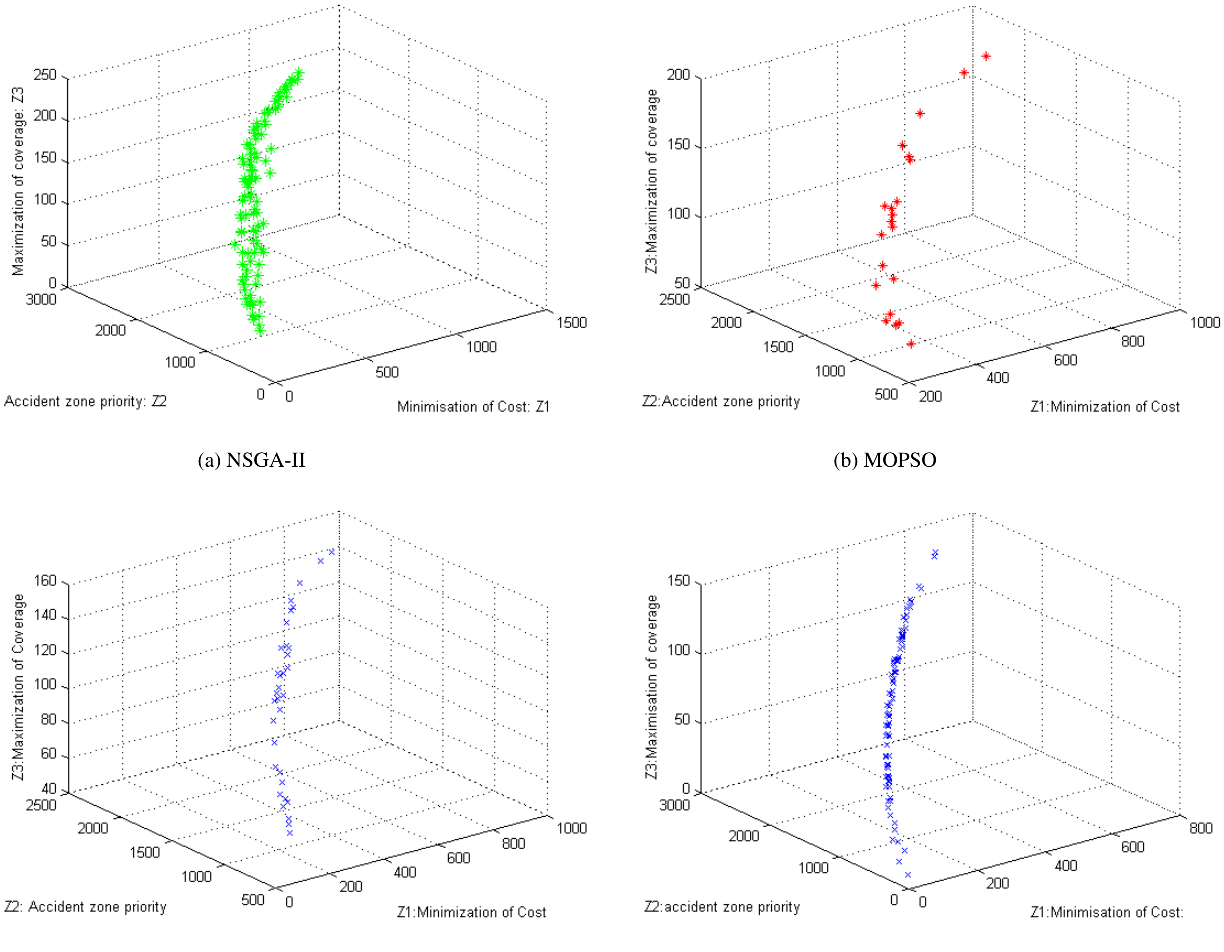
Numbers of RCPs	NSGA-II		MOPSO		PESA-II		SPEA-II	
	Avg	**Stdev**	**Avg**	**Stdev**	**Avg**	**Stdev**	**Avg**	**Stdev**
05	1.65e+00	1.03e+00	1.87e+00	1.27e+00	2.77e+00	1.72e+00	**9.36e-01**	**7.61e-01**
10	2.54e+00	1.91e+00	5.30e+00	4.04e+00	3.57e+00	3.30e+00	**1.99e+00**	**1.82e+00**
15	2.60e+00	1.65e+00	4.41e+00	3.62e+00	2.13e+00	1.18e+00	**1.77e+00**	**1.24e+00**

Table 9. Spread about RCPs

Numbers of RCPs	NSGA-II		MOPSO		PESA-II		SPEA-II	
	Avg	**Stdev**	**Avg**	**Stdev**	**Avg**	**Stdev**	**Avg**	**Stdev**
05	4.64e+02	4.55e+01	3.42e+02	2.91e+01	1.96e+02	3.14e+01	**3.34e+00**	**3.06e+00**
10	8.83e+02	1.05e+02	6.47e+02	7.07e+01	3.68e+02	8.93e+01	**2.16e+00**	**2.33e+00**
15	1.28e+03	9.23e+01	1.07e+03	1.38e+02	3.34e+02	5.14e+01	**9.61e-01**	**9.22e-01**

Table 10. Hypervolume about RCPs

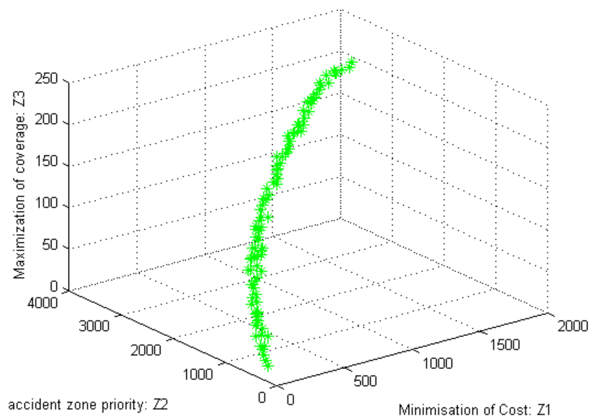
Numbers of RCPs	NSGA-II		MOPSO		PESA-II		SPEA-II	
	Avg	**Stdev**	**Avg**	**Stdev**	**Avg**	**Stdev**	**Avg**	**Stdev**
05	**3.02e+07**	**6.95e+06**	8.17e+06	1.62e+06	3.67e+06	9.81e+05	9.92e+06	2.31e+06
10	**1.48e+08**	**3.02e+07**	8.53e+07	1.36e+07	3.22e+07	1.18e+07	1.03e+08	2.93e+07
15	**4.49e+08**	**4.67e+07**	9.88e+07	7.01e+06	1.78e+07	7.24e+06	1.27e+08	5.89e+07



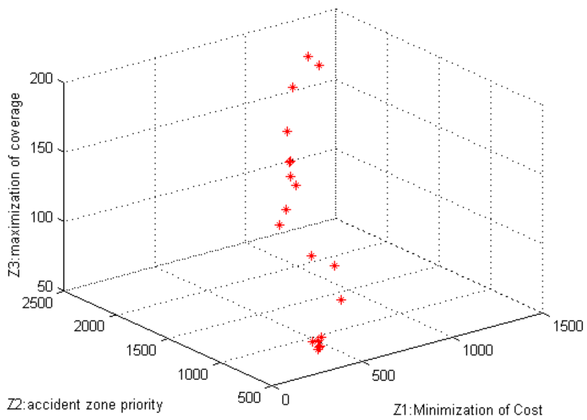
(a) NSGA-II (b) MOPSO

(c) PESA-2 (d) SPEA-2

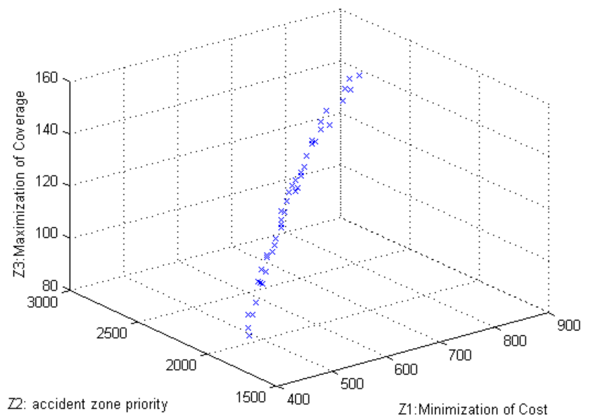
Figure 6. RCP pareto's front with 10 admissible positions



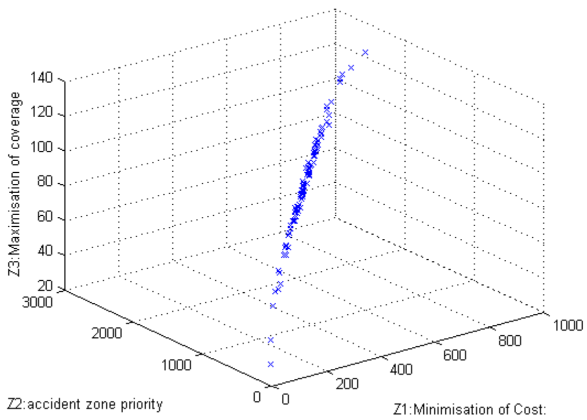
(a) NSGA II



(b) MOPSO



(c) PESA-2



(d) SPEA-2

Figure 7. RCP pareto's front with 15 admissible positions

of the IGDs shows that for the 05 and 10 admissible points, the PESA-II method is the most appropriate. SPEA-II is best for 15 admissible points. Compared to Spread, the PESA-II method is the best for the deployment for all scenarios. As for the hypervolume, the NSGA-II method is the best. Moreover, with respect to relay checkpoints, the comparison of the IGDs indicates that the SPEA-II is the most appropriate. It is also the best for comparing Spread. As for the hypervolume, the NSGA-II method is the best. Performance indicators have provided more specific orientations to users. Given the large number (i.e., 54) of these indicators, [44], have classified these according to their uses in optimization work. Also, in most of the works in the literature, it appears that Hypervolume is the best criterion of evaluation. This leads us to conclude that the NSGA-II method is the most suitable for the deployment of control points.

5. CONCLUSION AND FUTURE WORKS

At the end of this work, it appears that ITS can contribute to the regulation of activities in inter-urban road networks in developing countries. The control points are then defined for the collection, RCP and the TrCP of information in this context. We used the multi-objective formulation proposed in previous work for the deployment of control points. We then use the NSGA-II, MOPSO, SPEA-II, PESA-II methods to search among them, the one that would be best indicated for these deployments. Thus, we build the Pareto front for these deployments according to three scenarios: 05, 10 and 15 admissible points. We used three performance indicators namely IGD, Spread and Hypervolume. We noted that the NSGA-II is the preferred method for deploying these control points. Indeed, for all types of control points and for all scenarios, it offers the best results. The future works will consist in proposing an ontology of disturbances that occur in inter-urban road networks.

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