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# Energy loss optimization of run-off-road wheels applying imperialist competitive algorithm

*Hamid Taghavifar* *, *Aref Mardani*

*Department of Mechanical Engineering of Agricultural Machinery, Faculty of Agriculture, Urmia University, Urmia, Iran*

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ABSTRACT

The novel imperialist competitive algorithm (ICA) has presented outstanding fitness on various optimization problems. Application of meta-heuristics has been a dynamic studying interest of the reliability optimization to determine idleness and reliability constituents. The application of a meta-heuristic evolutionary optimization method, imperialist competitive algorithm (ICA), for minimization of energy loss due to wheel rolling resistance in a soil bin facility equipped with single-wheel tester is discussed. The required data were collected thorough various designed experiments in the controlled soil bin environment. Local and global searching of the search space proposed that the energy loss could be reduced to the minimum amount of 15.46 J at the optimized input variable configuration of wheel load at 1.2 kN, tire inflation pressure of 296 kPa and velocity of 2 m/s. Meanwhile, genetic algorithm (GA), particle swarm optimization (PSO) and hybridized GA–PSO approaches were benchmarked among the broad spectrum of meta-heuristics to find the outperforming approach. It was deduced that, on account of the obtained results, ICA can achieve optimum configuration with superior accuracy in less required computational time.



## 1. Introduction

Investigations propose that almost 20–55% of the energy developed to the drive tractor wheels is wasted in the tire–soil interaction [1]. This energy is not only wasted, however, the follow-on soil compaction produced by a portion of this energy may be damaging to crop yielding [2]. Soil and tire are subjected to consecutive deformations through wheel traversing over terrain, each of which, result in soil compaction and rolling resistance, respectively. The stability of soil, a substance of semi-infinite elasto-plastic medium behavior [3], is depending on acting mechanical loads on it. Soil loses its stability and gets irreversibly compacted if the load is great. Furthermore, tire deforms under the effect of applied load. The successive deformations cause tire to heat up and energy loss turns out that is known as rolling resistance in Terramechanics' terminology. Soil–wheel interactions are, however, the substantial contributor to occurrence of rolling resistance. Dissipated fuel due to mismanagement in the domain of agricultural tires was reported to be about 575 million liters per year in USA [4]. So far, many attempts have been conducted to predict rolling resistance theoretically [5–9] and empirically

* Corresponding author. Address: Department of Mechanical Engineering of Agricultural Machinery, Faculty of Agriculture, Urmia University, Nazloo Road, Urmia 571531177, Iran. Tel.: +98 441 2770508; fax: +98 441 277 1926.
E-mail addresses: ha.taghavifar@urmia.ac.ir, hamid.taghavifar@gmail.com (H. Taghavifa).

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[1,10–13], amongst which the joint intention was rolling resistance prediction through various modeling approaches. However, population-based evolutionary optimization assessments are required for minimization of energy waste due to rolling resistance.

Many of meta-heuristic techniques inspired by natural phenomena are proposed. Genetic algorithm (GA) motivated by Darwin's theorem is the most prominent optimization method. GA is formed based on endurance of fittest while its core ideology laid foundation by genetics and evolution behavior in biological reproductions [14]. Another popular stochastic method is particle swarm optimization (PSO) based on bird flocking and fish schooling [15]. PSO implements through initial populations (each called a particle) moving in search space. Each individual agent attempts to conquer the other particles and then evolution continues based on particle's and populations' experience for movement adjustment [15]. There are also too many algorithms introduced for evolutionary optimization including but not limited to harmony search (HS), ant colony optimization (ACO), and bee colony optimization (BCO).

In this paper we furnished a novel method as a substitute to the mentioned meta-heuristic revolutionary optimization techniques for energy waste minimization known as imperialistic competitive algorithm (ICA), first introduced by Atashpaz-Gargari and Lucas [16], which in essence, is inspired by human's social-political evolution. This algorithm, similar to any evolutionary algorithm, commences with a random initial population (country). Each representative of an empire is a country so that the countries are divided into a colony and imperialist indicates that colonies jointly come together as the empires. Imperialistic competitions among the empires form the basis of ICA, during which, weak empires collapse and powerful ones take possession of their colonies to the level that optimal points are possessed by the most powerful imperialist. It is noteworthy that to the best knowledge of authors, there is no study in literature dedicated to the optimization of energy efficiency of run-off-road wheels and the present study spearheads these analyses to serve as a catalyst for further investigations in this realm.

## 2. Collecting energy loss data

All the experimentations were performed in a long soil bin with the dimensions of 23 m length, 2 m width and 1 m depth applying a single-wheel tester mounted on a carriage [17]. A three-phase electromotor of 30 hp was used to power a carriage that accommodates the single-wheel tester. In order to provide the desired velocity, an inverter could adjust powering to the system and thus speed controlling transmitted through the chain system at sides of the soil bin. A Bongshin Model DBBP load cell with the capacity of 2000 kg, sensitivity of 0.1 kg and frequency of 50 Hz was situated vertically between a bolt power and the wheel-tester to measure the variations of dynamic load while traversing and adjusting the assigned values of wheel load as inputs. Four S-shape Bongshin Model DBBP load cells with 200 kg capacity were calibrated and then were placed at proper places horizontally in parallel pattern between carriage and single-wheel tester. These transducers were then interfaced to data acquisition system including Bongshin digital indicator BS7220 model connected to a port of RS232 Data Logger. The utilized tire was Good year 9.5L-14, 6 radial ply agricultural tractor tire. The system set up is shown in Fig. 1. The soil bin was filled with clay-loam soil as the predominant soil texture in Urmia, Iran. Tine, leveler and harrow were used to reverse soil bed to initial condition prior to each test run. Soil constituents and its properties are defined in Table 1. This experiment was conducted with the different velocities of 0.7, 1.4, and 2 m/s at three inflation pressures of wheel at three levels of 100, 200, and 300 kPa and five different wheel loads of 1, 2, 3, 4, and 5 kN on wheel tester with three replications in a complete randomized block design. Summary of treatments being tested is shown in Table 2. The experiment was conducted at the depth of measuring equal to 20 cm and at 12% moisture content.

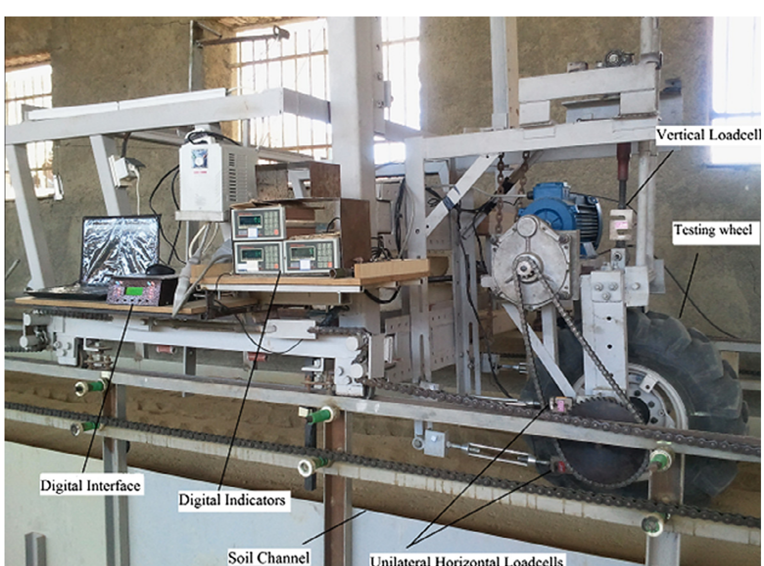


**Fig. 1 – The soil bin facility set up and its equipment.**

**Table 1 – Soil constituents and its measured properties.**

| Item | Value |
|---|---|
| Sand (%) | 34.3 |
| Silt (%) | 22.2 |
| Clay (%) | 43.5 |
| Bulk density (kg/m$^3$) | 2360 |
| Frictional angle (°) | 32 |
| Cone index (kPa) | 700 |

**Table 2 – Summary of experiment conducted.**

| Independent Parameters | | | Dependent parameter |
|---|---|---|---|
| Normal load (kN) | Inflation pressure (kP) | Velocity (m/s) | |
| 1 | 100 | 0.7 | |
| 2 | 200 | 1.4 | |
| 3 | 300 | 2 | Energy loss (J) |
| 4 | | | |
| 5 | | | |

Assessment of energy loss was based on direct measurement of rolling resistance and quantifying the waste power as following:

$$P = \frac{R \times dx}{dt} = R \times V \quad (1)$$

where $P$ is power, $R$ is rolling resistance ($N$) and $V$ is velocity (m/s). The loss of power is then used to calculate the loss of energy by knowing the time of wheel traversing as:

$$W = \int P dt \quad (2)$$

Hence,

$$W = \int RV dt \quad (3)$$

Therefore the measurement of rolling resistance and forward velocity are required to quantify the energy loss during wheel traversing.

## 3. Imperialist competitive algorithm

The optimization problem is proposed as to find the argument $x$ with its optimum cost $f(x)$ within the heuristic and meta-heuristic optimization algorithms. Imperialist competitive algorithm (ICA) was first introduced by Atashpaz-Gargari and Lucas [16] that has significantly been applied to various engineering applications. The aim in optimization is to reach the optimal value for the inputs. An array, which in genetic algorithm terminology is referred to "Chromosome" and in PSO "Particle", is generated in ICA known as country. The pseudo-code of this algorithm is described as follows.

### 3.1. Formation of initial empires

In a problem of $N_{var}$ dimensional the country is introduced as following.

$$\text{country} = [P_1, P_2, P_3, \ldots, P_{N_{variable}}] \quad (4)$$

The matrix of total countries is randomly formed as given.

$$\text{Country} = \begin{bmatrix} \text{country}_1 \\ \text{country}_2 \\ \text{country}_3 \\ . \\ . \\ . \\ \text{country}_N \end{bmatrix} = \begin{bmatrix} KP_1 & KI_1 & KD_1 \\ KP_2 & KI_2 & KD_2 \\ KP_3 & KI_3 & KD_3 \\ \vdots & \vdots & \vdots \\ KP_N & KI_N & KD_N \end{bmatrix} \quad (5)$$

Each country's cost is defined by evaluation of the cost function $f$ at variables $P_1, P_2, P_3, \ldots, P_{Nvar}$ to obtain the cost function as

$$\cos t_i = f(country) = f(P_1, P_2, P_3, \ldots, P_{N_{variable}}) \quad (6)$$

The initial countries are generated, $N_{country}$, to commence the algorithm. $N_{imp}$ number of the best population, (i.e. countries with the lowest cost function values), are allocated as empires. $N_{col}$ number of the remaining countries form the colonials each belong to an empire. The initial colonies are shared in proportion with each empire's power. To allocate the colonies, the normalized cost of imperialists is described as

$$C_n = \max_i\{c_i\} - c_n \quad (7)$$

where $c_n$, $\max_i\{c_i\}$ and $C_n$, and are the cost of $n$th imperialist, the highest cost among imperialists and the normalized cost of imperialists, respectively. Explicitly, the imperialist with the highest cost (weakest imperialist) denotes lower normalized cost. The relative normalized power of each imperialist, therefore, is defined by

$$P_n = \left| \frac{C_n}{\sum_{i=1}^{N_{imperialist}} C_i} \right| \quad (8)$$

Based on which, the colonies are allocated among the imperialists. From another perspective, the normalized power of each empire is the amount of colonies run by that. Accordingly, the initial number of each imperialist's colonies is described by

$$N.C._n = \text{round}\{P_n.N_{col}\} \quad (9)$$

where $N.C._n$ is the number of initial colonies of an imperialist and $N_{col}$ is the total number of colonies and round is a function that yields the round number if it is approximate. Fig. 2 shows the process of forming initial imperialists in which the powerful imperialists possess more colonies. Imperialist 1 is the most powerful among others that has possessed the highest number of colonies (see Fig. 2).

### 3.2. Assimilation

The assimilation policy follows to take in their colonies on the basis of social–political characteristics such as religion, culture and language. This part of ICA is shown in Fig. 3.

As the result of assimilation, the colony moves by $x$ unit in the direction of the imperialist to the new position of colony. Therefore is defined as

$$x \sim U(0, \beta \times d) \quad (10)$$

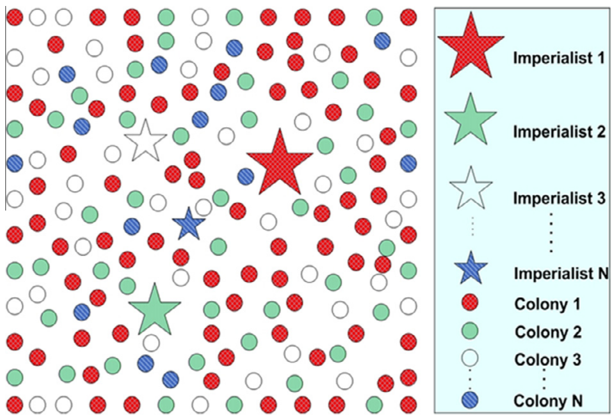


**Fig. 2 – Movement of colonies toward their relevant imperialists [16].**

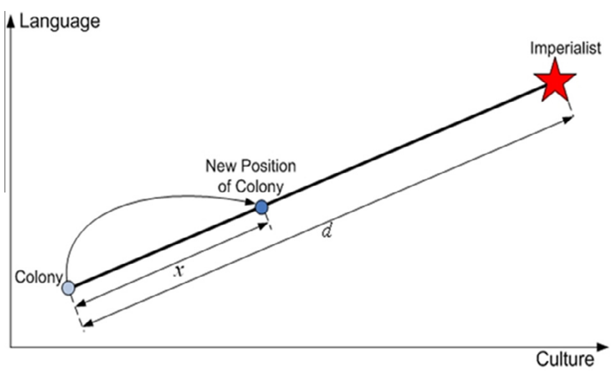


**Fig. 3 – Moving colonies toward their corresponding imperialist in randomly deviated direction [16].**

where $d$ is the distance between the colony and the imperialist, B is set between 1 and 2, however, $\beta > 1$ moves toward the imperialist from both of the vectors.

The absorption process, however, did not result in compliance with desires of imperialists. This implies that the real direction of movement toward the imperialist is not necessarily the shortest vector between the colony and the imperialist. These possible deviations in absorption are predicted in ICA by adding one random angle with uniform distribution, $\theta$, to the direction of colony's movement as described by

$$\theta \sim (-\gamma, \gamma) \tag{11}$$

where $\gamma$ can posses any random value, however, increased value causes more extensive searching around the imperialist and lower value causes the colony to move toward the imperialist closer to the connecting vector. In most of implementations, a $\theta$ value close to $\pi/4$ results in better convergence of colonies to the imperialist. The actual assimilation movement toward the imperialist is shown in Fig. 4.

### 3.3. *Replacement of colony and imperialist*

During the colony's movement toward the imperialist, it is possible that the colony can reach a lower cost function than imperialist. Then the imperialist and the colony would

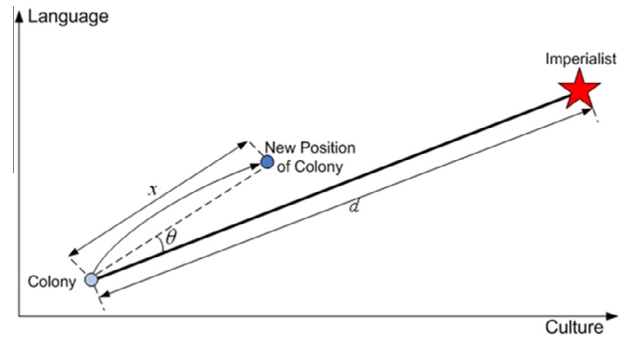


**Fig. 4 – The actual movement of colonies toward their corresponding imperialist [16].**

replace their positions. Thus, the algorithm continues with new colony and imperialist with the assimilation policy for newer colony and imperialist.

### 3.4. *The total power of an empire*

The total power of an empire equals with the power of an imperialist added with a certain percent of possessed colonies' power. Therefore the total cost of an empire is defined as

$$T.C._n = \mathrm{Cost}(\mathrm{imperialist}_n) + \xi \mathrm{mean}\{\mathrm{Cost}(\mathrm{colonies\ of\ empire}_n)\} \tag{12}$$

where $T.C._n$ is the total cost of $n$th empire, and $\xi$ is a positive value ranging between 0 and 1. Setting $\xi$ to a small value results in equalization of costs for the empire and the imperialist, where a high $\xi$ results the cost of empire to be highly affected by the colonies. $\xi = 0.05$ has given good results in most of implementations.

### 3.5. *Imperialistic competitions*

Each empire unable to increase the power defeats by the others during the imperialistic competition and ends is gradual collapse of the empire. That is, the weak empires lose their colonies and the powerful empires possess these colonies. Thus, one colony (can be more) of the weakest empire is competed to be possessed by a powerful empire (not necessarily the most powerful empire). Fig. 5 shows this process clearly.

In Fig. 5, empire 1 is the weakest empire and one of its colonies is competed to be possessed by one of empires 2 to $N$. In order to model the competition among the empires, the probability of possessing each empire is defined which is in proportion with the total power of the empire. The normalized total cost of an empire is defined as

$$N.T.C._n = \max_i\{T.C._i\} - T.C._n \tag{13}$$

where $T.C._n$ is the total cost of $n$th empire and $N.T.C._n$ is the normalized total cost. $T.C._n$ stands for the total cost of an empire where $N.T.C._n$ is the total power of an empire. Therefore, increase of $T.C._n$ has converse relation with $N.T.C._n$. Then the probability of possessing an empire ($P_{pn}$) is obtained by

$$P_n = \left| \frac{N.T.C._n}{\sum_{i=1}^{N_{imperialist}} N.T.C._i} \right| \tag{14}$$

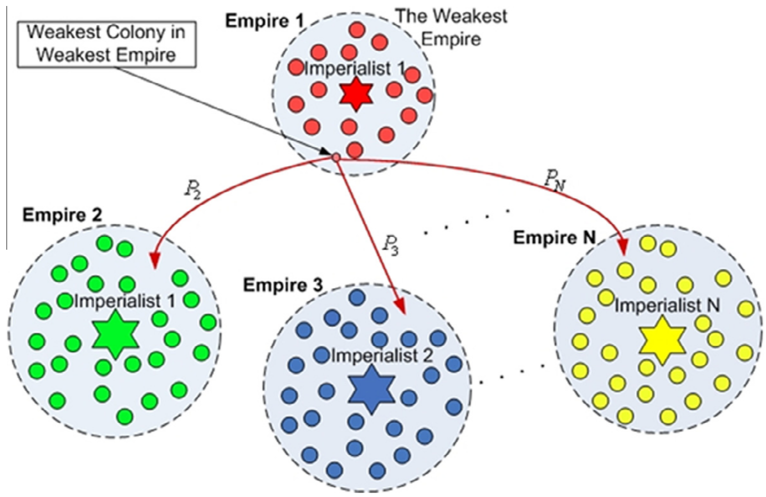


**Fig. 5 – Imperialist competition: The more powerful empire is more likely to occupy the weakest colony of the weakest empire [16].**

The vector P is formed based on the ($P_{pn}$) to share the colonies among the empires.

$$P = [P_{P1}, P_{P2}, P_{P3}, \ldots, P_{PN_{imp}}] \tag{15}$$

P vector is $1 \times N_{imp}$ dimensional. Then vector of $1 \times N_{imp}$ dimensional is formed. The arrays of vector are random values with uniform distribution in the range of [0,1].

$$R = [r_1, r_2, r_3, \ldots, r_{N_{imp}}] \tag{16}$$

$$r_1, r_2, r_3, \ldots, r_{N_{imp}} \sim U(0,1) \tag{17}$$

Then vector D is formed as following.

$$P = [P_{P1} - r_1, P_{P2} - r_2, P_{P3} - r_3, \ldots, P_{PN_{imp}} - r_{N_{imp}}] \tag{18}$$

The empire with the highest D vector index is the most powerful empire.

### 3.6. Collapse of weak empires

During the mentioned competitions, the empires lose their colonies to the more powerful ones. In ICA, there are conditions for collapse of an empire of them the most major one is to lose all the colonies.

### 3.7. Convergence

The algorithm continues to the point of reaching one of convergence conditions or reaching the described iterations. All empires gradually collapse and one empire stands as the most powerful empire and the countries are governed by a unique empire.

## 4. Designing the objective function

The core ideology of ICA or any evolutionary optimization is minimization of a described cost function (refer to 3. imperialist competitive algorithm), as affected by input variables. Regarding this, energy loss of run-off-road wheels obtained from experimentations is required to be described as a cost function to the ICA and other employed approaches. Hence, we used nonlinear regression analysis using SPSS 19 to obtain a function in terms of wheel load, tire inflation pressure and velocity.

$$E = (11.24 \times W) + (12.4 \times W^2) + (-22.5 \times \log(P)) + (83.3 \times V) \tag{19}$$

where $E$ is energy loss, $W$ is wheel load (kN), $P$ is inflation pressure (kPa) and $V$ is velocity (m/s). The statistical specifications of Eq. (19) are presented in Table 3. The adjusted-R square of the model was obtained 0.95.

## 5. Results and discussion

Defining the cost function of ICA by Eq. (19), country is simply described as a vector of input parameters.

$$\text{Country} = \begin{bmatrix} W_i \\ P_i \\ V_i \end{bmatrix} \tag{20}$$

**Table 3 – Analysis of variance (ANOVA) of multiple regression model for energy loss (J) at three levels of velocity, three levels of tire inflation pressure and five levels of wheel load.**

| Source of variation | DF | Sum of squares | Mean square | F-value |
|---|---|---|---|---|
| Regression | 3 | 417850.776 | 139283.592 | 178.468* |
| Residual | 41 | 31998.033 | 780.440 | |
| Total | 44 | 449848.809 | | |

* Significant at 0.05 probability level; DF, degree of freedom.

**Table 4 – Results of optimization.**

| Parameters of ICA | Number |
|---|---|
| Number of total countries | 80 |
| Number of initial imperialist countries | 4 |
| Number of iterations (epochs) | 30 |
| Revolution rate | 0.3 |
| Assimilation coefficient | 2 |
| Assimilation angle | 0.5 |
| Cost function | E (Eq. (19)) |

Countries then compete internally to minimize their costs to become the imperialist and denote the optimum level of input variables, followed by the external competition among imperialists resulting in occupancy of the imperialists by the one with the lowest cost function. Results of optimization are shown in Table 4. Fig. 6 shows the minimum and mean cost of imperialists. Also, Fig. 6 shows that the imperialist with the lowest cost function multitude of 15.46 J could occupy the other imperialists after seven iterations. Furthermore, GA approach was applied to the problem and the corresponding result is illustrated in Fig. 7. As appreciated from

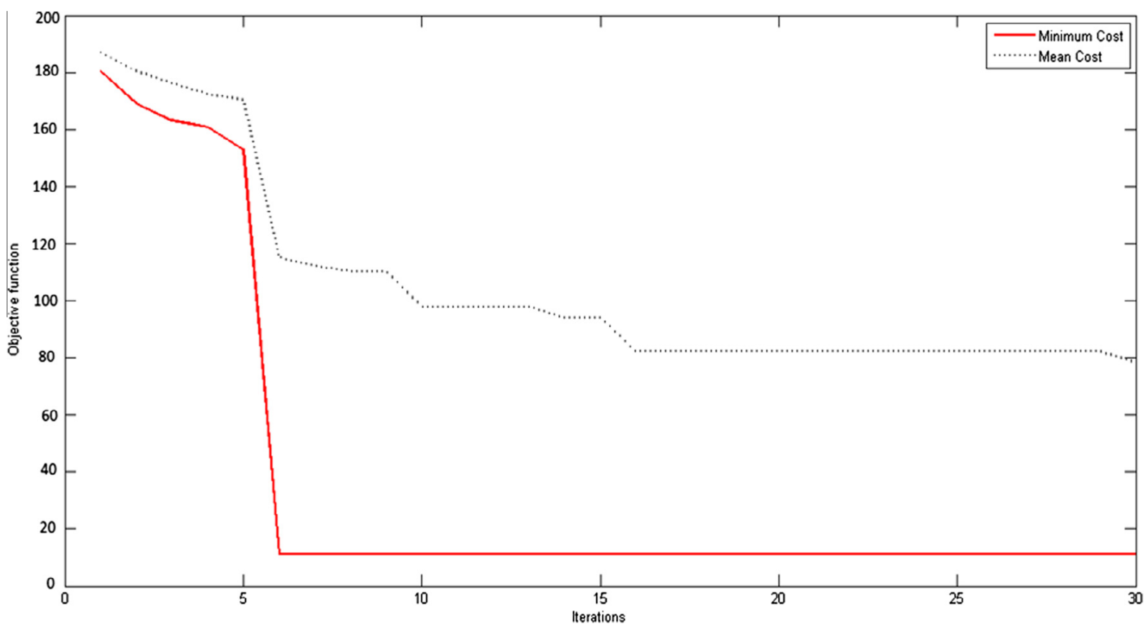


**Fig. 6 – Mean and minimum cost of all imperialists versus iterations for energy loss (J) by ICA approach.**

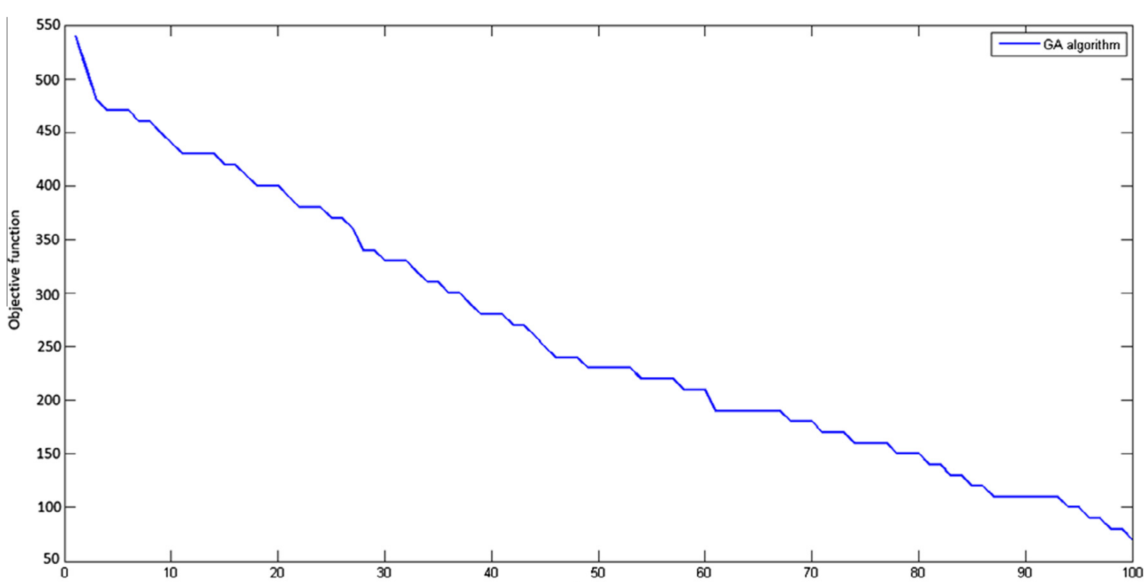


**Fig. 7 – Variation of objective function of energy loss (J) by GA versus iterations.**

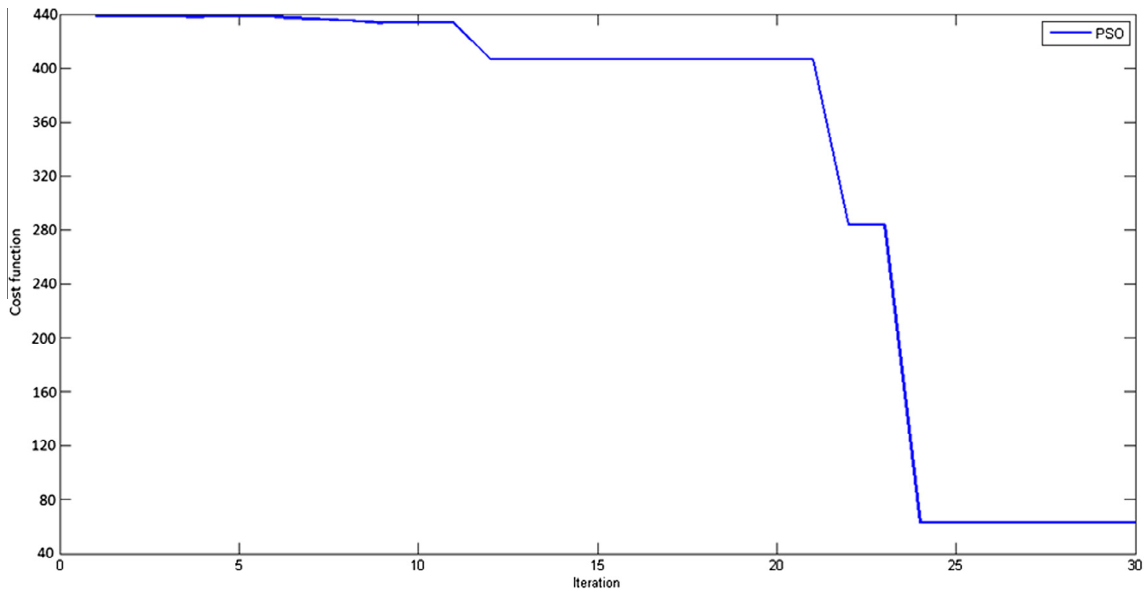


**Fig. 8 – Variation of cost function of energy loss (J) by PSO versus iterations.**

Fig. 7, GA has slow convergence to the optimal after 100 iterations when compared to ICA approach. Additionally, the minimized solution of the problem by GA methodology after 100 iterations is 76.84 J which confirms the supremacy of ICA over GA technique. The potential of PSO approach was assessed to find the optimum solution of the energy efficiency optimization problem of run-of-road wheels as depicted in Fig. 8. Fig. 8 proposes that after 30 iterations, energy loss has decreased from 438.51 to 67.92 J which is a weaker convergence to the optimal value in comparison with ICA method yet it yields more satisfactory answer when compared to GA method. Due to inherent advantages of GA and PSO methods reported in literature, it was decided to evaluate the ability of hybridized GA–PSO method and make comparison between the aforementioned techniques. However, the implementation resulted in a significantly better performance of GA–PSO comparing with discrete GA and PSO methodologies (Fig. 9). Sharper convergence after 8 iterations propose that GA–PSO possesses the both advantages of GA and PSO methods, however, the minimized amount of problem obtained by this method is 41.97 which is greater than ICA method. It is concluded that ICA method outperformed the other employed methods in the present study. Moreover, it should be added that the improved performance of GA–PSO could be attributed to the selection of particle populations of PSO as chromosome weights of GA which allows better chromosomes to be included in the next generation and this evolution continues to reach the final answer.

Fig. 10 shows that at wheel load of 1 kN, inflation pressure of 300 kPa and velocity of 2 m/s, the imperialist with the low-

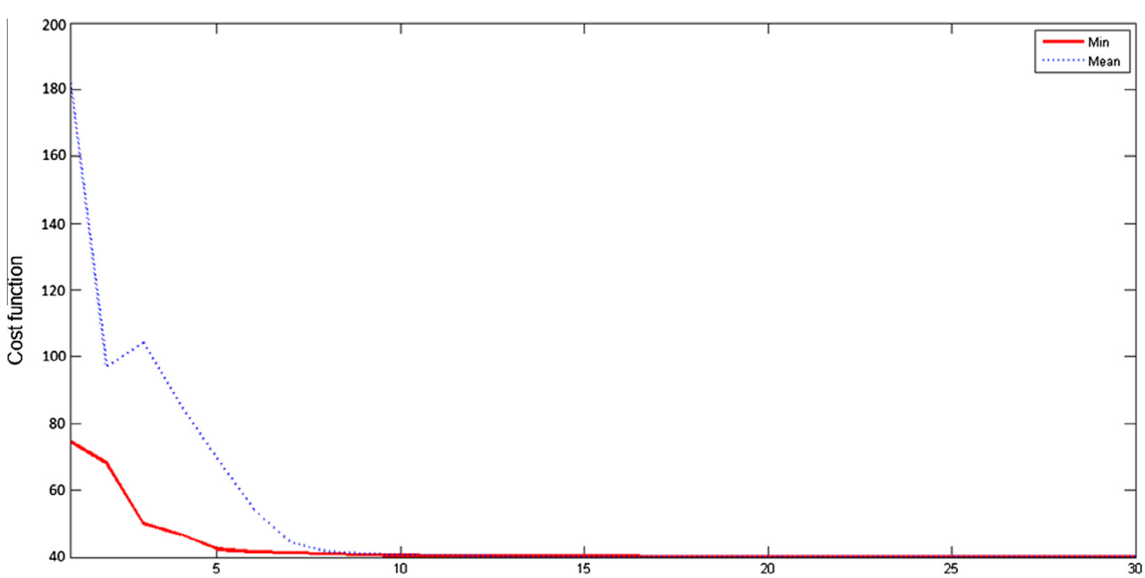


**Fig. 9 – Variation of cost function of energy loss (J) by GA–PSO versus iterations.**

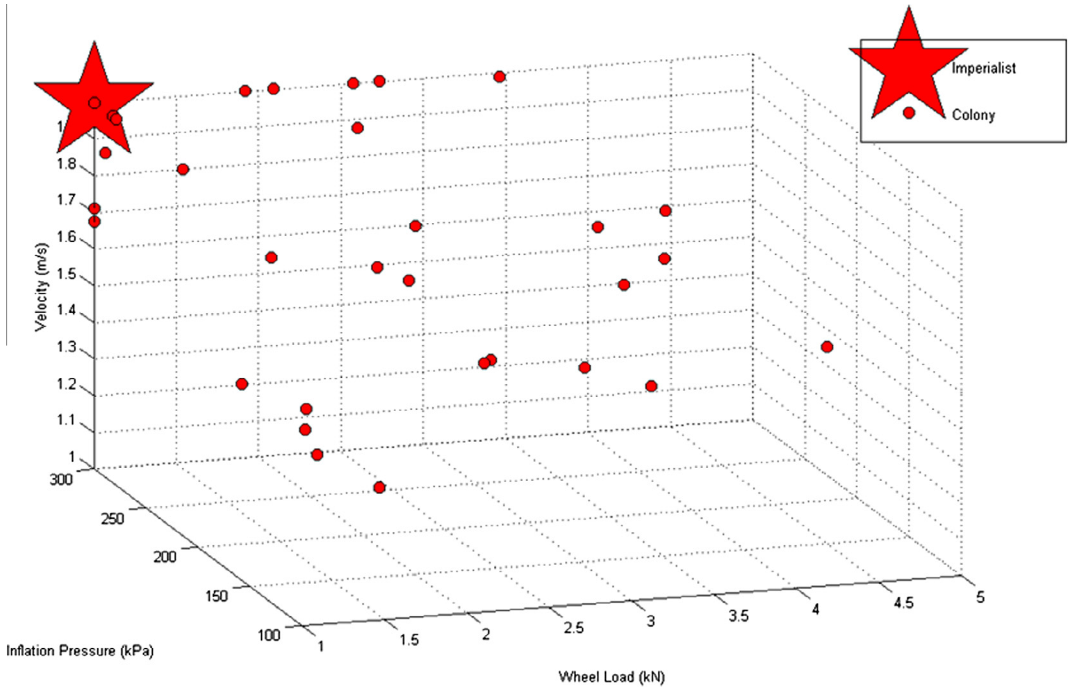


**Fig. 10 – Occupancy of the weak imperialists by the imperialist with the lowest cost function in the search space including wheel load, inflation pressure and velocity.**

est cost function could possess other imperialists and form its empire and the including colonies (this is shown in ICA search space). Also optimization results showed that minimized energy loss of 15.46 J was obtained at wheel load of 1.2 kN, inflation pressure at 296 kP and velocity at 2 m/s. This also suggests that energy loss has nonlinear relationship with velocity and tire inflation pressure that necessitates the adoption of stochastic meta-heuristic approaches for problem optimization.

## 6. Concluding remarks

Amongst the most well-known meta-heuristic techniques of genetic algorithm (GA), stochastic particle swarm optimization (PSO), ant colony optimization (ACO) and bee colony optimization (BCO), we selected GA, PSO and hybrid GA–PSO due to their documented abilities to compete with the recently introduced imperialist competitive algorithm (ICA) for minimization of run-off-road wheel energy loss in a soil bin facility. The results divulged that ICA far succeeded in finding good results in a less iteration number compared to other evolutionary methods. We concluded the following in regard with ICA superiority.

- The drawbacks of pre-maturity and unpredictability in GA and bias of final results in PSO (due to requirement for initial guessing of particles) is overcome by ICA.
- Unlike GA, PSO and GA–PSO, ICA is independent of saving the previous location of agents. This increases its convergence speed.
- ICA determines the movement direction of agents by the best vector in empire (among pre-defined agents). This is performed in PSO in local and global vectors. The vector in ICA changes for different agents which results in exploration ability, while in PSO it is constant for all the agents in iteration. This, in turn, increases ICA's accuracy over PSO.

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