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Estimation of tracked vehicle suspension parameters

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ABSTRACT. This work aims to estimate the suspension stiffness and damping coefficient of a tracked vehicle by using an inverse problem technique based on Particle Swarm Optimization (PSO) and on Random Restricted Window (R2W). The tracked vehicle has ten road wheels. Each road wheel is linked to a passive and independent suspension. A half car model with seven degrees of freedom describes the bounce and pitch dynamics of the chassis and the vertical dynamics of the wheels. Bounce and pitch accelerations are evaluated when the vehicle traverses a bump terrain. The inverse problem approach minimizes the total quadratic error between estimated and pseudo-experimental data for bounce and pitch accelerations. The viability of a field experiment to estimate the suspension parameters is analyzed, as well as the performance of the employed optimization methods and the effects of the noise on pseudo-experimental data.

Keywords: vehicle suspension, inverse problem, R2W, PSO.

Estimativa de parâmetros da suspensão de um veículo sobre lagartas

RESUMO. Este trabalho objetiva estimar a rigidez e o coeficiente de amortecimento da suspensão de um veículo sobre lagartas. Técnicas de problema inverso são empregadas, sendo utilizados os métodos de otimização *Particle Swarm Optimization* (PSO) e *Random Restricted Window* (R2W). O veículo sobre lagartas tem dez rodas. Cada roda está ligada a uma suspensão passiva e independente. Um modelo de meio carro com sete graus de liberdade descreve a dinâmica vertical de cada roda e a dinâmica vertical e de arfagem do chassi. As acelerações vertical e de arfagem do chassi são avaliadas quando o veículo passa sobre um terreno com uma lombada. A abordagem de problema inverso minimiza o erro quadrático total entre os dados estimados e os dados pseudo-experimentais referentes às acelerações vertical e de arfagem do chassi. A viabilidade de um experimento de campo para estimar os parâmetros da suspensão é analisada, sendo também analisados o desempenho dos métodos de otimização utilizados e o efeito do ruído sobre os dados pseudo-experimentais.

Palavras-chave: suspensão veicular, problema inverso, R2W, PSO.

Introduction

The logistics and maintenance costs of military tracked vehicles motivate the study of field experiments to evaluate vehicle subsystems performance. These vehicles should be on service as long as possible without field maintenance and without return to the maintenance facility. Moreover, mainly in a combat situation, the consequences associated to premature failure of components of such a vehicle can be dire (Woldman, Tinga, Van Der Heide, & Masen, 2015). Then, monitoring the vehicle performance, prior a mechanical failure, a criterion to shutdown maintenance could be established. In this sense, this work proposes and analyzes the viability of a field experiment to evaluate vehicle suspension parameters. In this experiment, the vehicle traverses a bump terrain, while bounce and pitch accelerations are measured. Knowing such data and employing an inverse problem approach, the estimation of the suspension stiffness and damping coefficient could be feasible. The same idea can be used in non-military tracked utility vehicles such as tractors, crane vehicles and snow vehicles.

The vehicle suspension is devoted to minimize the vibrations imposed by the terrain, influencing the comfort and maneuverability of the vehicle (Ata & Oyadiji, 2014; Dhir & Sankar, 1994; Gillespie, 1992; Goga & Klucik, 2012; Mehdizadeh, 2015; Ryu, Park, & Suh, 2011). The suspension takes the entire vehicle weight and offers a flexible support to the vehicle on the ground (Sridhar & Sekar, 2006). In this mechanical system, the suspension stiffness and damping coefficient are relevant parameters to analyze the suspension wear. However, these parameters cannot be directly measured when the vehicle is in field. To overcome this problem, an inverse problem approach could be adopted.

The inverse problem techniques are powerful tools to estimate properties of a system by using indirect measurements (Ozisik & Orlande, 2000). So, chassis bounce and pitch accelerations can be measured to estimate the suspension stiffness and damping coefficient. To solve the inverse problem, an optimization method minimizes the sum of square errors between estimated data and experimental data.

The optimization of vehicle suspension parameters had been conducted by using a stochastic optimization method (Goga & Klucik, 2012). Thus, considering the inverse problem a special kind of an optimization problem, the adoption of a stochastic optimization method could be a promising choice to estimate the suspension parameters of a tracked vehicle.

The stochastic optimization methods Random Restricted Window (R2W) and Particle Swarm Optimization (PSO) are employed in the present work. Both methods create populations of possible solutions, which are updated to minimize the objective function. R2W creates a new population in a limited region of the search space in the vicinity of the better solution of the last population (Bihain, Camara, & Silva Neto, 2012) and PSO mimics a flock of birds looking for food (Colaço, Orlande, & Dulikravich, 2006; Moraes & Nagano, 2012). These optimization methods are useful to deal with high nonlinear objective functions and do not require the evaluation of the gradient of these functions. Furthermore, these methods are easy to be implemented. Otherwise, in these methods, empirical parameters must be set and they usually have high computational cost (Colaço et al., 2006).

Material and methods

The direct problem is represented by a half car model with five road wheels (Ata & Oyadiji, 2014). This model has seven degrees of freedom, taking into account the follow assumptions: the chassis is a rigid body; the terrain is rigid; the roll and yaw movements are not considered; the wheels stiffness and the suspensions stiffness are constants; the suspension damping coefficient is constant; and the damping effects of the wheels are not considered.

The model describes half vehicles with N wheels. Equations (1) and (2) model bounce and pitch dynamics of the chassis and Equation (3) models the bounce dynamics of each wheel i.

$$m_b\ddot{Z}_b + \sum_{i=1}^{N} C_b\left(\dot{Z}_b + l_i\dot{\theta} - \dot{Z}_{wi}\right) + \sum_{i=1}^{N} K_b(Z_b + l_i\theta - Z_{wi}) = 0 \qquad (1)$$

$$I_y\ddot{\theta} + \sum_{i=1}^{N} C_b\left(\dot{Z}_b + l_i\dot{\theta} - \dot{Z}_{wi}\right)l_i + \sum_{i=1}^{N} K_b(Z_b + l_i\theta - Z_{wi})\, l_i = 0 \qquad (2)$$

$$m_w\ddot{Z}_{wi} - C_b(\dot{Z}_b + l_i\dot{\theta} - \dot{Z}_{wi}) - K_b(Z_b + l_i\theta - Z_{wi}) + K_w(Z_{wi} - Z_{ri}) = 0 \qquad (3)$$

where

m_b is the mass of the chassis, Z_b is the bounce displacement of the center of gravity (C.G.) of the chassis, θ is the pitch angle of the chassis, Z_{wi} is displacement of the wheel i, I_y is the chassis inertia, m_w is the mass of the wheel, l_i is horizontal distance between the chassis C.G. and the suspension i, C_b is the damper coefficient and K_b is the suspension stiffness.

The terrain excitation (z_{ri}) on each wheel follows Equations (4), (5) and (6) (Ata & Oyadiji, 2014).

$$z_{ri}(t) = z_{r1}(t + \tau_i) \qquad (4)$$

$$z_{r1}(t) = \begin{cases} h\left\{1 - \cos\left[\left(2\pi\frac{v}{w}\right)(t - 0.5)\right]\right\}, & 0.5 \le t \le 0.5 + w/v \\ 0, & \text{otherwise} \end{cases} \qquad (5)$$

$$\tau_i = {(l_1 - l_i)}/{v} \qquad (6)$$

where

the excitation delay (τ_i) is a function of the vehicle velocity (v) and of the distance between the first suspension (l_1) and the suspension i (l_i). Furthermore, the bump with height h and width w is modeled in Equation (5).

The initial condition of the ordinary differential system of equations is the mechanical equilibrium. Moreover, the system of ordinary differential equations is solved by a fourth order Runge-Kutta algorithm implemented in SciLab software.

Table 1 furnishes the values of the constants for the half car model adopted in the present work, which are based on the M113 armored vehicle (Ata & Oyadiji, 2014).

Table 1. Constants of the half car model.

Parameter	Symbol	Value
Chassis mass (kg)	m_b	5109
Chassis inertia (kgm^2)	I_y	12856
Wheel mass (kg)	m_w	113.5
Wheel stiffness (N m^{-1})	K_w	613000
First suspension position* (m)	l_1	1.35
Second suspension position* (m)	l_2	0.69
Third suspension position* (m)	l_3	0.02
Fourth suspension position* (m)	l_4	−0.66
Fifth suspension position* (m)	l_5	−1.32
Bump height (m)	h	0.1
Bump width (m)	w	0.5
Vehicle velocity (km h^{-1})	v	10

*The horizontal distance between the chassis C.G. and the suspension i.

The exact values and the limits of the search spaces of the estimated suspension parameters are present in Table 2.

The proposed inverse problem is an optimization problem, which is solved by using PSO or R2W. The optimum solution determines the estimated damping coefficient and suspension stiffness.

Table 2. Exact values and limits of the search spaces of the suspension parameters.

Parameter	Symbol	Exact	Lower limit	Upper limit
Damping coefficient (Ns m^{-1})	C_b	22520	1000	30000
Suspension stiffness (N m^{-1})	K_b	104000	10000	150000

PSO describes the movement of a particle swarm searching the minimum of an objective function, taking into account the individual and global learning process. In other words, the better experiences of each particle and of the population are considered. In this method, each particle j is identified by a position, x, and by a velocity, λ (Colaço et al., 2006). The position and the velocity of the particles are updated following

$$\lambda_j^{k+1} = \propto \lambda_j^k + \beta\, r_{1,j}(P_j^k - x_j^k) + \beta\, r_{2,j}(P_g - x_j^k) \quad (7)$$

$$x_j^{k+1} = x_j^k + \lambda_j^{k+1} \quad (8)$$

In Equations (7) and (8), the inertial parameter α and the learning parameter β controls the update process of the particles, while the stochastic characteristic of the method is introduced by $r_{1,j}$ and $r_{2,j}$, which are random numbers within the range [0, 1] with uniform distribution. The superscript k identifies the optimization process iteration. P_j^k is the best candidate solution found in the history of the particle j and P_g is the best candidate solution in the population (Colaço et al., 2006). The evolution process of the population is repeated until the stopping criterion is satisfied.

R2W is based on a random population of possible solutions, which is generated in a restricted region of the search space. The best candidate solution of the population is found and the population is discarded. Then, a new random population is created in a limited region of the search space around the last best candidate solution. This procedure is repeated until the stopping criterion is satisfied (Bihain et al., 2012).

The R2W population evolves by using Equations (9) to (11).

$$P_L = P_g - \delta P_g \quad (9)$$

$$P_H = P_g + \delta P_g \quad (10)$$

$$x_j = P_L + R_j (P_H - P_L) \quad (11)$$

where

δ is the restriction factor, which is an empirical constant used to define the size of the search domain for each parameter, P_L is an array with the lowest values of the parameters in the search domain, P_H is an array with the highest values of the parameters in the search domain and R_j is an array of random numbers within the range [0, 1] with uniform distribution (Bihain et al., 2012).

Figures 1 and 2 show simplified flowcharts for PSO and R2W.

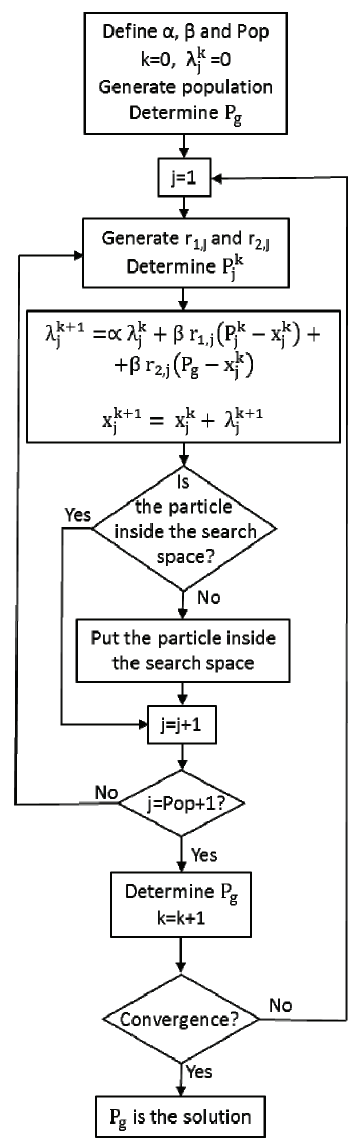

Figure 1. PSO flowchart.

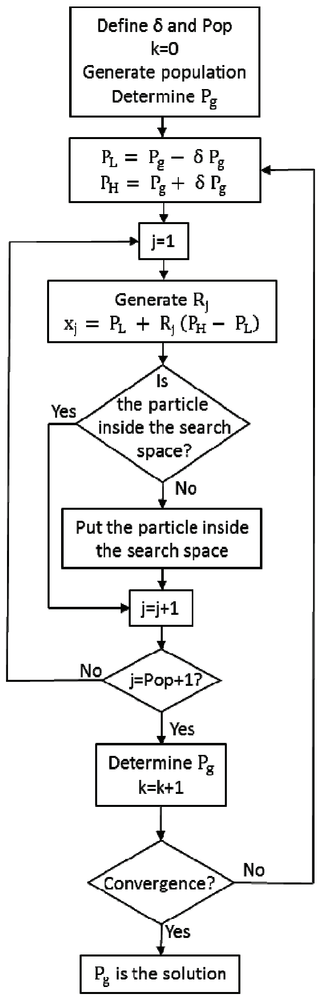

Figure 2. R2W flowchart.

The objective function, Equation (12), evaluates the total quadratic error between the estimated and the pseudo-experimental data (Ozisik & Orlande, 2000) for bounce and pitch accelerations, considering a dimensionless form

$$S(K_b^k, C_b^k) = \frac{1}{2n}\sqrt{\sum_{i=1}^{n}\left[\left(\frac{\ddot{Z}(K_b^k, C_b^k) - \ddot{Z}_{exp}}{\max|\ddot{Z}_{ref}|}\right)^2 + \left(\frac{\ddot{\theta}(K_b^k, C_b^k) - \ddot{\theta}_{exp}}{\max|\ddot{\theta}_{ref}|}\right)^2\right]} \quad (12)$$

where

$\max|\ddot{\theta}_{ref}|$, $\ddot{\theta}_{exp}$ and $\ddot{\theta}(K_b^k, C_b^k)$ are, respectively, the maximum absolute value of the pitch acceleration furnished by the reference data (Ata & Oyadiji, 2014), the pseudo-experimental pitch acceleration and the estimated pitch acceleration. Similarly, $\max|\ddot{Z}_{ref}|$, $\ddot{Z}_{exp}$ and $\ddot{Z}(K_b^k, C_b^k)$ are, respectively, the maximum absolute value of the bounce acceleration furnished by the reference data (Ata & Oyadiji, 2014), the pseudo-experimental bounce acceleration and the estimated bounce acceleration. Furthermore, n is the number of measurements along of the time for bounce and pitch accelerations.

The pseudo-experimental data mimics experimental data and they are simulated measurements obtained from the solution of the direct problem by using a priori prescribed values for the unknown parameters (Chisaria, Macorinib, Amadioa, & Izzuddinb, 2015; Machado & Orlande, 1998; Ozisik & Orlande, 2000). The pseudo-experimental data are evaluated by using

$$\ddot{\theta}_{exp} = \ddot{\theta}_{exact} + \omega\, E \max|\ddot{\theta}_{exact}| \quad (13)$$

$$\ddot{Z}_{exp} = \ddot{Z}_{exact} + \omega\, E \max|\ddot{Z}_{exact}| \quad (14)$$

In Equation (13) and (14) the subscript exact refers to the proposed numerical solution obtained with the exact values of the suspension parameters K_b and C_b. Moreover, ω is a random variable with normal distribution, zero mean and unitary standard deviation, E is an arbitrary noise level (Machado & Orlande, 1998; Ozisik & Orlande, 2000).

The inverse crime is present in inverse problems when the same mathematical solution is used for computing both pseudo-experimental data and estimated data (Chávez, Alonzo-Atienza, & Álvarez, 2013). However, in the present work, the inverse crime is avoided by introducing random noise in Equation (13) and (14).

Despite of the inverse crime, the noiseless data (E = 0) can be used to verify the correct implementation of the inverse problem solver and to select the better empirical constants of the optimization method.

The stopping criterion of the optimization procedure considers that Equation (15) must be satisfied during 60 consecutive iterations

$$|S(K_b^k, C_b^k) - S(K_b^{k-1}, C_b^{k-1})| / S(K_b^{k-1}, C_b^{k-1}) \leq 0.01 \quad (15)$$

or the discrepancy principle, represented by Equation (16), must be satisfied

$$S(K_b^k, C_b^k) \leq 10^{-6} \quad (16)$$

Results and discussion

The results of the direct problem established in Equations (1) to (6) for bounce and pitch accelerations are compared with reference data (Ata & Oyadiji, 2014) in Figures 3 and 4. In these figures, percentage errors between Reference and Simulation results are also shown. The agreement between these results indicates that the proposed numerical solution represents correctly the chassis dynamics.

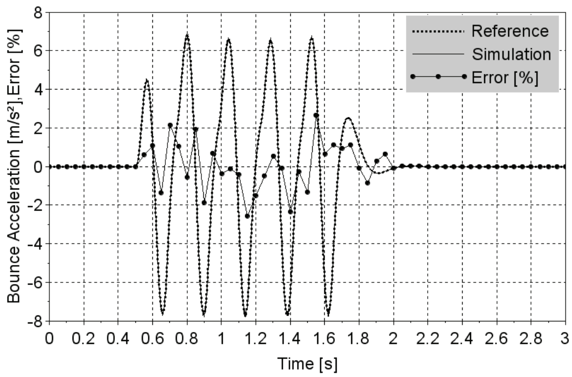

Figure 3. Bounce acceleration.

In R2W, the restriction factor (δ) and the number of elements of the population (Pop) are empirical constants. The influences of these empirical constants on the optimization process can be analyzed from Table 3, where estimated damping coefficient and suspension stiffness are present. Noiseless pseudo-experimental data are considered to perform these estimations. Populations with 10, 20 and 40 elements are analyzed, as well as the restriction factor equal to 0.005, 0.006 and 0.008. All of the estimated parameters have shown relative error lower than 0.15%. Moreover, the discrepancy principle was satisfied, stopping the optimization procedure. So, in this work, the restriction factor equal to 0.008 and the population size equal to 20 particles are chosen, because these empirical constants have spent less computational time.

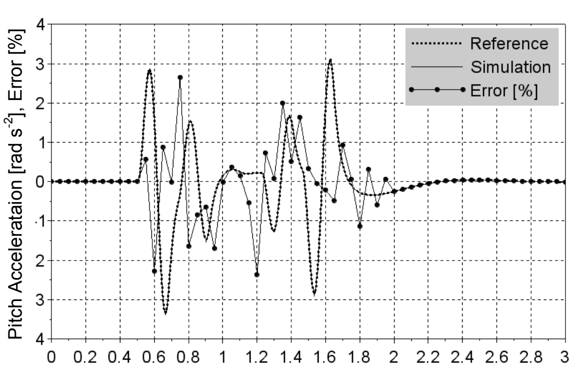

Figure 4. Pitch acceleration.

In PSO, the population size (Pop), the inertial parameter (α) and learning parameter (β) are empirical constants that must be chosen to perform the inverse problem. The conditions1 ≤β≤ 2 and 0 ≤α≤ 1 are recommended (Colaço et al., 2006).

The influences of PSO empirical constants on the estimation of the suspension parameters were investigated for noiseless pseudo-experimental data. Simulations with β equal to 1.2, 1.5, 1.8 and 2.0 and with α equal to 1.0 were performed, but they have not converged. Furthermore, the influence of the population size on the inverse problem is summarized in Table 4, considering β=1 and α=0.5.

The Table 4 show that the best results were computed with 20 particles in the population, minimizing better the objective function. Consequently, in this work, the selected values of the PSO empirical constants were β = 1, α = 0.5 and Pop=20.

The results shown in Tables 3 and 4 reveal that the relative error between the exact values of the suspension parameters and the estimated ones are minor than 0.16%. Thus, the proposed inverse problem approach, employing PSO and R2W, with noiseless pseudo-experimental data, has estimated correctly the suspension parameters.

The effects of noise on pseudo-experimental data are summarized in Tables 5 and 6. The discrepancy principle was not satisfied in these results. However, the relative errors of the estimated parameters were less than the noise level, indicating that the proposed inverse problem approach was very efficient by using R2W or PSO. Nevertheless, increasing the noise level, the relative errors in the estimated parameters are also increased. Furthermore, increasing the noise level, the number of iterations to reach the convergence is reduced, but the converged value of the objective function is increased. It is explained by the convergence criterion established by Equation (15). It is expected, since increasing measurement errors, the pseudo-experimental data become worst, limiting the minimization process of the objective function.

Comparing the results shown in Tables 5 and 6, it is verified that R2W spent more computational time than PSO for the cases with noise level equal to 0, 1 and 5%. In these cases, R2W revealed higher values for objective function and for relative errors of estimated parameters. Otherwise, for 10% of noise level, R2W has shown better results for estimated parameters. Nevertheless, considering only the computed values for objective function, both methods have furnished similar results.

The evolutions of the objective function by using PSO and R2W were presented in Figures 5 and 6 for the cases reported in Tables 5 and 6. These figures show that increasing the noise level, the convergence is faster, but the minimum value of the objective function increases. In addition, PSO and R2W performances were similar in these studied cases.

Table 3. Influences of the restriction factor and population size on R2W.

Pop	δ	C_b (Ns m^{-1})		K_b (N m^{-1})		S	Time (s)	k
		Estimated	Relative error	Estimated	Relative error			
	0.005	22511	-0.04%	103915	-0.08%	1E-6	3751	56
10	0.006	22526	0.03%	103852	-0.14%	9E-7	2334	34
	0.008	22519	0.00%	103996	0.00%	8E-8	2582	38
	0.005	22530	0.04%	104064	0.06%	1E-6	5470	40
20	0.006	22521	0.01%	104026	0.03%	2E-7	7555	55
	0.008	22521	0.00%	103960	-0.04%	2E-7	1502	11
	0.005	22521	0.01%	103997	0.00%	1E-7	6303	23
40	0.006	22523	0.02%	103875	-0.12%	6E-7	3038	11
	0.008	22518	-0.01%	104021	0.02%	2E-7	4797	17

Table 4. Influences of the population size on PSO.

Pop	C_b (Ns m^{-1})		K_b (N m^{-1})		S	Time (s)	k
	Estimated	Relative Error	Estimated	Relative Error			
10	22525	0.02%	103850	-0.14%	7E-7	3106	43
20	22521	0.00%	104039	0.04%	2E-7	1626	11
40	22519	-0.01%	104158	0.15%	6E-7	1372	4

Table 5. Noise effects on R2W (δ=0.008 and Pop=20).

Noise	C_b (Ns m^{-1})		K_b (N m^{-1})		S	Time (s)	k
	Estimated	Relative Error	Estimated	Relative Error			
0%	22521	0.004%	103960	-0.039%	2E-7	1502	11
1%	22533	0.056%	104657	0.631%	6E-5	7230	101
5%	22557	0.163%	103894	-0.102%	2E-4	5067	71
10%	22571	0.229%	107571	3.433%	6E-4	4168	61

Table 6. Noise effects on PSO (β=1, α=0.5 and Pop=20).

Noise	C_b (Ns m^{-1})		K_b (N m^{-1})		S	Time (s)	k
	Estimated	Relative Error	Estimated	Relative Error			
0%	22521	0.003%	104039	0.038%	2E-7	1626	11
1%	22526	0.028%	103997	-0.003%	6E-5	4933	68
5%	22531	0.049%	103927	-0.070%	2E-4	4755	67
10%	22640	0.531%	98421	-5.365%	6E-4	4596	64

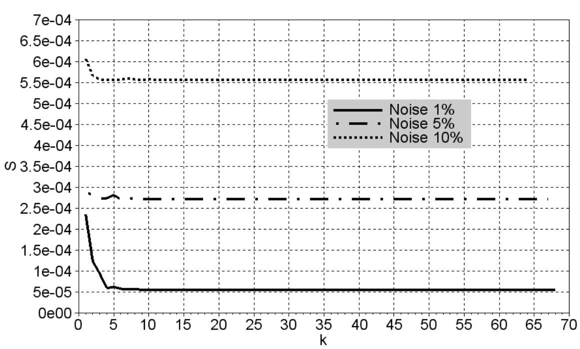

Figure 5. Objective function evolution using PSO.

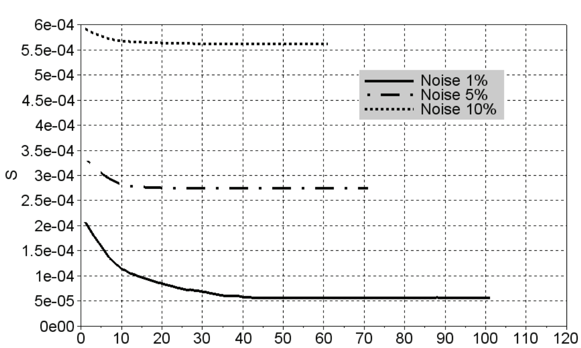

Figure 6. Objective function evolution using R2W.

Conclusion

In the present work, a field experiment to estimate the damping coefficient and the suspension stiffness of a tracked vehicle with ten road wheels was proposed based on an inverse problem approach by using stochastic optimization methods: PSO and R2W.

A half car model represents the direct problem, whose solution was compared with a reference solution. Vehicle bounce and pitch accelerations were correctly simulated.

The empirical constants of the optimization methods were analyzed, permitting the selection of the best ones for each studied method.

The performance of PSO and R2W were also analyzed, considering pseudo-experimental data with different noise levels. PSO and R2W had shown similar results. However, in most of the cases, R2W had spent more computational time, but for 10% of noise level, R2W have shown low relative error, spending less computational time.

It is important to note that, in the noise cases, the relative errors of the estimated parameters have always been lower than the noise level. Thus, theoretically, the measurement errors were not amplified in the proposed inverse problem solution.

The noiseless cases have converged, satisfying the discrepancy principle. Otherwise, for 1, 5 and 10% of simulated random noise, the convergence was reached when negligible variations of the objective function during 60 consecutives iterations were verified. Such strategy has conducted to higher objective function values for the cases with noise, but has permitted the convergence.

The results have shown the viability of the proposed field experiment with the inverse problem approach to estimate the suspension parameters. This information could be used to predict the vehicle shutdown maintenance.

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References

Ata, W. G. K., & Oyadiji, S.O. (2014). An investigation into the effect of suspension configurations on the performance of tracked vehicles traversing bump terrains. *Vehicle System Dynamics, 52*(7), 969-999.

Bihain, A. L. J., Camara, L. D. T., Silva Neto, A. J. (2012). Avaliação da rotina inversa R2W na estimação de parâmetros de transferência de massa no processo de adsorção de glicose e frutose. *Tendências em Matemática Aplicada e Computacional, 13*(3), 277-289.

Chávez, C. E., Alonzo-Atienza, F., & Álvarez, D. (2013). Avoiding the inverse crime in the inverse problem of electrocardiography: estimating the shape and location of cardiac ischemia. *Computing in Cardiology, 40*(1), 687-690.

Chisaria, C, Macorinib, L, Amadioa, C, & Izzuddin, B. A. (2015). An inverse analysis procedure for material parameter identification of mortar joints in unreinforced masonry. *Computer & Structures, 155*(15), 97-105.

Colaço, J. M., Orlande, H. R. B., & Dulikravich, G. S. (2006). Inverse and optimization problems in heat transfer. *Journal of the Brazil Society of Mechanics Science and Engineering, 28*(1), 1-24.

Dhir, A., & Sankar, S. (1994). Ride dynamics of high-speed tracked vehicles: simulation with field validation. *Vehicle System Dynamics, 23*(1), 379-409.

Gillespie, T. D. (1992). *Fundamentals of vehicle dynamics*. Warrendale, PA: Society of Automotive Engineers.

Goga, V., & Klucik, M. (2012). Optimization of vehicle suspension parameters with use of evolutionary computation. *Procedia Engineering, 48*, 174-179.

Machado, H. A., & Orlande, H. R. B. (1998). Inverse problem for estimating the heat flux to a non-newtonian fluid in a parallel plate channel. *Journal of the Mechanical Society of Mechanical Sciences, 20*(1), 51-61.

Mehdizadeh, S. A. (2015). Optimization of passive tractor cabin suspension system using ES, PSO and BA. *Journal of Agricultural Technology, 11*(3), 595-607.

Moraes, M. B. C., & Nagano, M. S. (2012). Cash balance management: A comparison between genetic algorithms and particle swarm optimization. *Acta Scientiarium. Technology, 34*(4), 373-379.

Ozisik, M. N., & Orlande, H. R. B. (2000). *Inverse heat transfer*. New York, US: Taylor & Francis.

Ryu, S., Park, Y., & Suh, M. (2011). Ride quality analysis of a tracked vehicle suspension with a preview control. *Journal of Terramechanics, 48*(6), 409-417.

Sridhar, S. S., & Sekar, N. S. (2006). Optimisation of kinematics for tracked vehicle hydro gas suspension system. *Defence Science Journal, 56*(5), 743-752.

Woldman, M., Tinga, T., Van Der Heide, E., & Masen, M. A. (2015). Abrasive wear based predictive maintenance for systems operating in sandy conditions. *Wear*, 338-339, 316-324.

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