Dynamic synthesis of a multibody system: a comparative study between genetic algorithm and particle swarm optimization techniques

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Abstract. This paper proposes a dynamic synthesis of a flexible multibody systems, mainly, a slider crank mechanism incorporating a flexible connecting rod. Differently to classical synthesis, the mechanism design variables are identified by means of the mechanism dynamic responses such as, the velocity and the acceleration of the slider, and the flexible connecting rod transversal deflection. A comparative study between two optimization techniques, the genetic algorithm (GA) and the Particule Swarm optimization (PSO), has been established. The two approaches employ different strategies and computational effort to find a solution to a given objective function. Thus, we are interested in the comparison of their implementation.The comparative study asserts that the PSO technique is more suitable for the dynamic synthesis.

Key words: Flexible slider crank mechanism, dynamic synthesis, PSO, GA.

1 Introduction

Synthesis of multibody systems presents a stiff problem. Thus, regard to the tremendous constraints required for this problem resolution, representing a burdensome task to handle with. For some industrial applications, such as medical applications, welding and manufactering robot, the mechanism reliability is highly required. Usually, the multibody synthesis is established by means of a kinematic modelling. Thereby, the described path of the mechanism is optimized subject to a desired path. Consequently, the mechanism parameters, involved in the described path, are optimized in order to handle as maximum as possible with the desired path. However, for the applications mentioned above, the kinematic synthesis presents many shortcomings. This is referred to the non consideration of the inevitable clearance in the joint, also, the elastic behaviour of its different components. For high velocity, the clearance has a significant impact on the mechanism response [1]. Thus, the mechanism synthesis deploying simply the generated path has major drawbacks.

Many works has been completely devoted to multibody synthesis by means of optimization techniques. Laribi et al [2] have focused on a four bar mechanism synthesis. An hybrid algorithm coupling the genetic algorithm to the fuzzy logic has been developed for this aim. Recently, Essomba et al [3] have deployed the genetic algorithm for a spherical parallel mechanism, used in medical applications, synthesis. Kucuk [4] has used the particle swarm optimization in order to reduce the consumed energy for a 3-RRR parallel manipulator.

This work deals with a dynamic synthesis of a flexible slider crank mechanism. The optimal mechanism design variables are defined based on a desired dynamic response for more reliability. The main advantage of the dynamic synthesis is that, it take into account the real imperfections subsumed in a real mechanism and involve them in the optimization process.

A comparative study between two optimization techniques is presented in this work. The genetic algorithm and the particle swarm optimization have been performed for the mechanism synthesis. The slider velocity and acceleration, as well as, the transversal deflection of the connecting rod have been chosen as dynamic responses deployed for the mechanism identification.

1Mathematical modelling

The dynamic modelling of the multibody systems has been the object of numerous works.

The differential algebraic equations combine both, ordinary differential equations (ODE) and algebraic equations. Ordinary differential equations describe the multibody systems responses. Thereby, algebraic equations are responsible for geometrical modelling of the mechanism.

In this work, a flexible slider crank mechanism is used as a demonstrative exemple. The synthesis of the mechanism design variables is carried out based on the mechanism dynamic response.

Lagrangian coordinates for the used mechanism are depicted in figure 1.

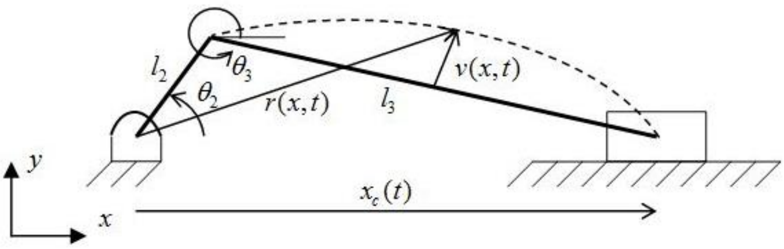


Fig. 1 Flexible slider crank mechanism

The Hamilton principle yields :

$$\begin{bmatrix} M & \Phi_q^T \\ \Phi_q & 0 \end{bmatrix} \begin{bmatrix} \ddot{q} \\ \lambda \end{bmatrix} = \begin{bmatrix} Q_e + Q_v \\ Q_c \end{bmatrix} \tag{1}$$

$$\Phi(q,t) = 0 \tag{2}$$

$$Q_{vi} = \sum_{j=1}^{2} \lambda_j \frac{\partial \varphi_j}{\partial q_i} \tag{3}$$

Whrein, Q_v, Q_e are respectively The total constrained forces and The total applied forces.

The constraint equations, for the slider crank mechanism, which are a system of one degree of freedom, with holonomic constraints based on general coordinates, is as follow:

$$\Phi(q,t) = \begin{pmatrix} \varphi_1(q,t) \\ \varphi_2(q,t) \end{pmatrix} = \begin{pmatrix} l_2 \cos\theta_2 + l_3 \cos\theta_3 - x_c \\ l_2 \sin\theta_2 + l_3 \sin\theta_3 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix} \tag{4}$$

2 Objective function

The synthesis problem, is formulated as an optimization problem. Thus, the design parameters (the crank and flexible connecting rod lengths) involved in the dynamic response are obtained in order to reduce the error between the desired response and the optimal one,by mean of the used optimizations techniques.

The mechanism response, mainly the slider velocity or the acceleration or the midpoint transversal deflection of the connecting rod, has been represented for, about two crank revolutions.

The error is measured between every point of the optimal solution obtained with the optimization technique and the target one.

The objective function is presented in the following form:

$$F = \min(Error) \tag{5}$$

$$Error = \sqrt{\frac{1}{n}\sum_{i}\left[{x_i - x_{i\,target}} \Big/ {Max(x_i) - Min(x_i)} \right]^2} \tag{6}$$

Where, x_i,$x_{itarget}$ and n represent respectively the proposed design variables response, the target response and the number of measured points in the response.
The error value is dimensionless, therefore,the proposed objective function can be applied for different dynamic responses involved along the identification process.

3 Optimization approachs

In this work, two optimization techniques have been carried out. A comparative study has been made between the genetic algorithm and the particle swarm optimization.

The genetic algorithm has been the most used heuristic optimization technique for a long time, mainly due, to the simplicity of its implementation. It is divided into the following steps:

Intial population choice :

The initial population in this work is constituted of 20 individuals. Each individual is a vector of two parameters. These parameters are the crank length and the flexible connecting rod length.

Evaluation and selection :

All the initial chosen individuals are evaluated by means of the objective function. A selection probability will be then affected to each individual referring to its performance [5]. Consequently, a high selection probability will be attributed to better individual to favourite their selection for the crossover. However, the selections of low performance individuals remain possible.

Crossover:

Along the crossover process, the two selected individuals exchange each other some characteristics. The crossover probability is equal to 0.9 in this work.

Mutation :

The mutation aim to ensure that the proposed solution is a global optimum. Thus through modifying just a single component of the design variables vector, the individual can be situated in a position far away to its vicinity in the search space. This lead to investigate a broader area of potential global optimum. The mutation probability is equal to 0.3.

The PSO (particle swarm optimization) technique is inspired from the swarm displacement phenomenon. It has been proved that, for a swarm, every particle moves beyond and toward particles in its neighbourhood. Thus, these particles are called informers. Reffering to these informers, the velocity and position can be updated. In accordance to the natural swarm, for the oprimization using PSO, every particle is matched to her own informers. A confidence coefficients are involved for the communication as well as, the particles positions and velocities update. In fact, thanks to informants, all the swarm particles are connected together. Thus, the swarm is similar to a network allowing the communication between the leader of the swarm (best located particle) with the rest of the swarm. The evolution of every particle performance contributes for the swarm guidance in order to reach the best existant position. Indeed, every particle contains a number of parameters to optimize. In this work, the crank and the connecting rod length are the parameters to optimize. Each position represents a solution, and the swarm moves among the defined search space. In every iteration for the PSO algorithm, the positions and the velocites of all paticles are updated as the following equation[6] :

$$v_d = c_1 v_d + c_2(p_d - x_d) + c_3(g_d - x_d) \tag{7}$$

$$x_d = x_d + v_d \tag{8}$$

Where ,c_1,c_2 and $c_3$are confidances coefficient, x_d , v_d , are respectively the position and the velocity p_d , g_d are respectively the best position found by the particle and the best position found by informants of the particle.

4 Results and discussion

The dynamic synthesis has been carried out by means of three different dynamic responses. Two design variables are involved in the mechanism synthesis, mainly, the crank and the flexible connecting rod lengths. An enlarged search interval has been chosen for the aforementioned design variables. The synthesis is made regard to a reference mechanism of a crank length of 50 mm and a flexible connecting rod of 350 mm.

Genetic algorithm results

The interval search has been chosen as [10;90] and [100;900] respectively for the crank and the flexible connecting rod lengths. A set of 20 individuals has been randomly considered from the search interval mentioned above.

Based on the mechanism response, the design variables identification has been established. In each iteration, the algorithm evaluates the proposed design variables (l1, l2) performance, and error between the proposed and the reference mechanism responses is measured thanks to the objective function.

As illustrated in figure 2.a the minimization evolution of the objective function subject to iteration number reachs an error of about 6.68 10^{-3}. The proposed lengths after 250 iterations, are 49.09 and 361.2 mm, respectively for the crank and the connecting rod. Using an intel I7 3.4GHz with 8 Gb of RAM, the CPU time is about 909 sec.

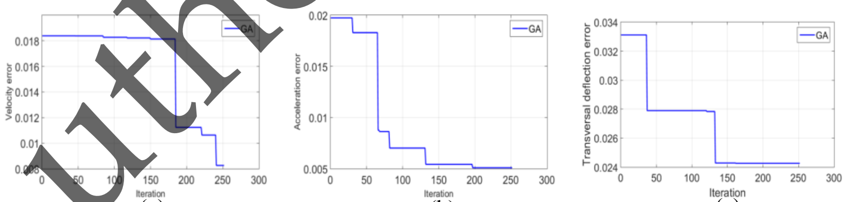
It is worth mentioning that the mechanism synthesis can be also conducted using the slider acceleration. As it can be seen in figure 2.b, an error of 5.105 10^{-3}has been reached after 250 iterations. The algorithm proposes a couple of 49.292 mm and 339.06 mm respectively for the crank and the connecting rod lengths for a CPU time of 1092 sec. The mechanism synthesis deploying the transversal deflection of the connecting rod presents the most onerous synthesis for the proposed algorithm. Thus, based only on a single body elastic deformation (due to eigen mode exicitation), doesn't allow to the mechanism to carter for the required reliability. Therefore, the algorithm reachs an error of 1.99 10^{-2} after 250 iterations as shown in figure 2.c. Otherwise, a couple of 47.54 mm and 363.18 mm respectively for the crank and the connecting rod lengths are proposed for a CPU time of 1148 sec.

As it can be drawn, for the proposed interval search, the genetic algorithm doesn't match perfectly with high accuracy, in spite of, an exhibited convergence.

Table 1. Proposed design variables using the genetic algorithm optimization

	The crank length (mm)	*The connecting rod length (mm)*	*Error*	*CPU time (sec)*
Acceleration synthesis	49.29	339.06	5.105 10^{-3}	1092.7
Velocity synthesis	49.09	361.2	6.68 10^{-3}	909.54
Transversal deflection synthesis	47.54	363.18	1.99 10^{-2}	1148.9

A higher performance optimization technique should be investigated to overcome the genetic algorithm weakness, in order to propose better accurate results.



(a) (b) (c)

Fig. 2 Optimization error evolution: (a)based on the velocity, (b)based on the acceleration ,(c)based on the transversal deflection

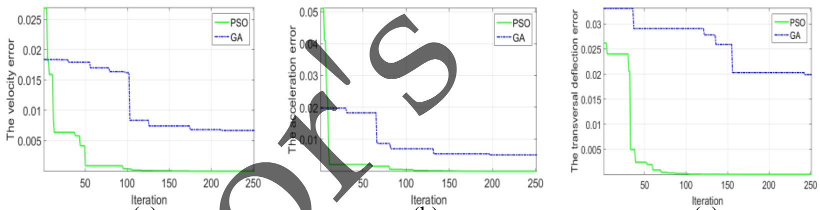
PSO optimization results

This section is completely devoted to the dynamic synthesis using the particle swarm optimization.

In order to perform a comparative study between the GA and PSO, a set of 20 particles as well as 250 iterations has been fixed along the particle PSO algorithm execution. As evident in figure 3.a, for the PSO optimization, the algorithm converges in almost 50 iterations beside 170 for the genetic algorithm. Moreover, the proposed design variables are exactly the same ones of the reference mechanism in about 5.19 10^3 sec. However, the required CPU time is significantly higher than time consumed for the GA. This represents an interesting tradeoff accuracy/ CPU time.

Similary to the dynamic synthesis deploying the GA, the PSO synthesis is able also to identify the mechanism response, based on the slider acceleration. Figure 3.b exhibits the mechanism synthesis based on the slider acceleration. The algorithm convergence is reached in about 25 iterations. Beside an error of 5.105 10^{-3} for the GA, the PSO garentuees an error of 5.851 10^{-9}, matching perfectly with the reference mechanism dimensions.

Regarding to the most burdensome synthesis type for the GA, based on the transversal deflection of the connecting rod, the PSO algorithm overcomes the diffuclities faced, proposing exactly the same design variables as these of the reference mechanism. As illustrated in figure 3.c, for an error of 1.6193 10^{-8} beside 1.995 10^{-2} for the GA, the PSO presents a very performant tool for the mechanism optimization in spite of its high consumed calculation time.



(a) (b) (c)

Fig. 3 Optimization error evolution: (a)based on the velocity, (b)based on the acceleration ,(c)based on the transversal deflection

Table 2. Proposed design variables using the PSO optimization

	The crank length(mm)	*The connecting rod length(mm)*	*Error*	*CPU time (sec)*
The velocity synthesis	50	350	2.7345e-08	5.19 10^3
The acceleration synthesis	50	350	5.851e-09	7.27 10^3
The transversal deflection synthesis	50	350	1.6193e-08	7.29 10^3

Conclusion

This work denotes an insight into the multibody system synthesis. For this purpose, the flexible slider crank mechanism has been deployed as a demonstrative exemple. Some conclusions can be drawn:

- For an enlarged interval search, the mono-objective optimization using the genetic algorithm do not provide reliable results for the dynamic synthesis, mainly, for the transversal deflection synthesis. The genetic algorithm provides the best design variables results based on the slider acceleration.
- The PSO optimization provides more accurate results comparing to the GA. Moreover, the algorithm convergence is reached in almost few iterations, and the algorithm converges exactly to the reference mechanism parameters.

It is observed that, from an evolutionary point of view, the performance of the PSO is better than that of GA. The PSO seems to arrive at its final parameter values in fewer generations than the GA. Compared to GA, the advantages of PSO are that it is easy to implement and there are few parameters to adjust.

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