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To cite this article: N H Tho *et al* 2019 *IOP Conf. Ser.: Mater. Sci. Eng.* **530** 012013

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Research on Determination of Optimum Parameters for The Lower Extremity Exoskeleton

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Abstract. Lower extremity exoskeleton is a device that enables the user to sit down without the need of using a chair. The design of the exoskeleton has to satisfy multiple objectives, many of which are defined by the body of the user. Most CAD (Computer aided design) programs nowadays still have not added multiple-objective evolutionary algorithms (EAs). This paper presents an application of NSGA-II (Non-dominated sorting genetic algorithm II) and AMO (Adaptive-Multiple objectives) in order to solve the problem of multiple-objective optimization in designing Lower extremity exoskeleton. Moreover, the Box-Behnken design (BBD) - based response surface methodology was also used to investigate the effects of the number of initial samples, the number of samples per iteration and the maximum number of iterations on AMO. Then, the Pareto-optimal frontier of feasible points was carried out for the alternative solutions of design problem. In addition, the TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution) method was employed in order to support the decision makers in deciding the engineering optimum parameters. The optimum parameters obtained are $\alpha_{\min} = 24.81^\circ$, $\alpha_{\max} = 115.08^\circ$ and $\alpha_{\text{stand}} = 177.2^\circ$. With the same input values, AMO and NSGA-II gave the same output values, however the number of samples which are used to determine convergence of AMO only equals to 0.66 that of NSGA-II. The method in this study is advantageous for multiple-objective optimization in CAD problems.

Keywords: MOGA, NSGA-II, AMO, exoskeleton, product design.

1. Introduction

In the 1960s, the USA's Ministry of Defense began to care about expanding human capacities. First, they started developing exoskeletons that allowed soldiers to carry more weight [1]. More than military purposes, researchers also focused on medical services [2]. Nowadays, the rate of older workers or old people in general having bone and joint related problems is rising. According to the population report of General Statistics Office of Viet Nam, Viet Nam has passed population aging period since 2017 [3]. Therefore, the need of developing an exoskeleton for elders has increased over time. At the moment, there is already an exoskeleton developed with this particular purpose in mind [4] (Figure 1), robot HAL [5], a device that helps you sit down, design and manufactured by Noone company [6], Archelis of NITTO [7]. However, the lower extremity of the exoskeleton is not compatible with Vietnamese's body, the price's also too high. Therefore, designing a lower extremity



that satisfies multiple objectives is necessary. The optimum designs have become more and more important during the last three decades. Multiple objective problems are becoming more popular. The interval method is usually used in multi-objective problems, however, it needs a large amount of calculations and consumption time. In this particular issue, the split method in Solidworks needs to perform 43,281,400 mathematical calculations. Here, the problem has 4 decision variables, 3 objectives and 1 constraint, this number exceeds the program's capacity. In order to solve the problem, the intervals must be large enough and the amount of calculations must be reduced. This process requires careful analysis of the given data, then deciding the intervals to achieve the optimum parameters. The computational capacity of computers and human are not always able to solve any problem. Therefore, algorithms like the Golden-section search method, coordinate search algorithm, method of steepest descent and genetic algorithm (GA) were developed to overcome the above difficulties.



Figure 1. Lower extremity LegX of Ekso [2].

In the mentioned algorithms, the genetic algorithm based on the non-dominated sorting procedure (NSGA-II) has been proven to be most efficient. NSGA-II combined with Kriging is called AMO – adaptive multi-objective optimization, it is available in ANSYS simulation tool of CAE (computer aided engineering). This paper will connect the visual aspect of design in Solidworks and the AMO algorithm of ANSYS, thence solving the problem of optimizing multiple objectives in the design of the lower extremity.

2. Mathematical model

In Viet Nam, Military Technical Academy (MTA) is one of the first institutes to research and develop the exoskeletons. With government investment, the exoskeleton that the MTA developed is focused on military purposes and helping the disabled ones. In order for the exoskeletons to become usable, there must be a large investment and support from all sources to properly research and test in all conditions. However, there are few researches with the purpose of supporting workers and elders in Viet Nam in the particular manner. The exoskeleton can be split into two kinds: The lower extremity and upper extremity. The reason is because of how the two parts of the body operate. The arms – upper extremity are for flexible and exact jobs. The legs – lower extremity are for moving mostly [8].

The main objective of the paper is the lower extremity of the exoskeleton that helps the body to squat or crouch. The exoskeleton must not obstruct the body from moving around; moreover, it must support the body and acts like a moving chair.

The lower extremity is described in Figure 2. In which, a is the length of the thigh, b is the length of the leg, c is the locking mechanism, and d is the support mechanism. These dimensions are illustrated in Figure 2 and Figure 3.

Table 1. The targets of the lower extremity.

	c	β	Target
Lowest sitting point	215 mm	135°	20°
Highest sitting point	356 mm	135°	120°
Standing point	374.5 mm	45-90°	180°

The exoskeleton has three targets: the lowest angle of the thigh when squatting is 20° and the highest one is 120°. When the legs are straight, the respective angle is 180°. When you walk, the angle will vary between 180° and 120°, depends on the analysis of stepping sequences [9]. And there is one constraint, when standing the γ angle must be smaller than 180°. Table 1 describes the values and the targets of the mathematical model. The decision factors a , b , d and their limits are shown in Table 2.

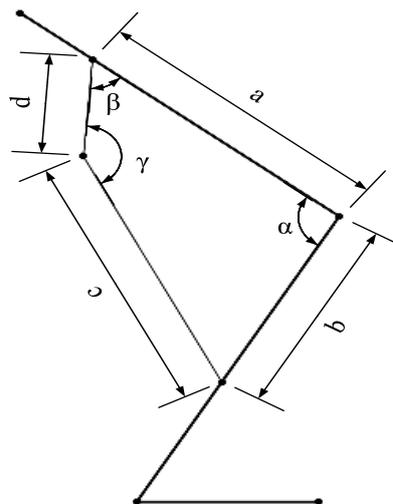


Figure 2. Principle model of the lower extremity.

The objective function α of the three levels: Lowest sitting point, highest sitting point, and standing point are displayed in its most basic form in equation 1.

$$\alpha = \arccos\left(\frac{a^2 + b^2 - f^2}{2 \times a \times b}\right) \quad (1)$$

where, f is the side calculated from equation 2.

$$f = \sqrt{d^2 + c^2 - 2 \times d \times c \times \cos(\gamma)} \quad (2)$$

and γ angle is calculated from equation 3.

$$\gamma = \arccos\left(\frac{d^2 + e^2 - a^2}{2 \times d \times e}\right) + \arccos\left(\frac{c^2 + e^2 - b^2}{2 \times e \times c}\right) \quad (3)$$

Table 2. Values and their limits.

Parameters	Minimum values (mm)	Maximum values (mm)
a	5	485
b	5	485
d	1	150

**Figure 3.** Dimensions of the locking mechanism.

3. Research methodology

3.1 Kriging Algorithm

Kriging [10] is a model algorithm combining with the response surface method (RSM). This method is suitable for changing variables that have a significant effect on the output values. It is an exact two-way interpolation function that combines a polynomial model like response surfaces – giving a global model of the design space and a local deviation, then interpolate the planning points. Kriging has the ability to screen the inputs continuously, including the real values. However, it does not support discrete variables. The efficiency of Kriging depends on the ability to estimate the internal error to improve the quality of the response surfaces by creating the screening points and putting them into the areas that need them the most.

3.2 MOGA (Multi-Objective Genetic Algorithm)

MOGA is a variant of NSGA-II (Non-dominated sorting based genetic algorithm II) that depends on the notation of controlling the dominating individuals [11]. It supports all kinds of input values. The Pareto chart is performed using the rapid classification method. The method of solving the constraints uses the dominated rule and entirely depends on the targets. Therefore, this method does not use penalty functions and Lagrange method. Because of that, the feasible solutions are always ranked based on the priority. The MOGA's flowchart is displayed in Figure 4.

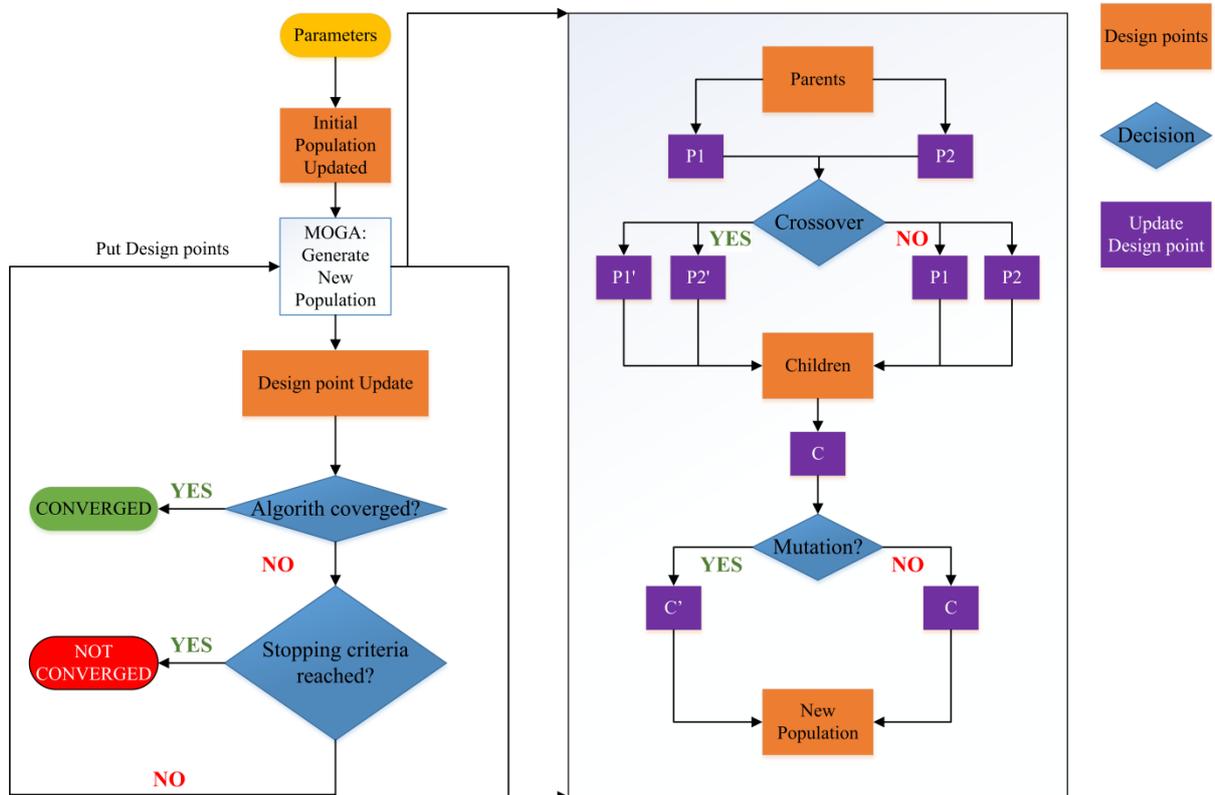


Figure 4. MOGA flowchart (adapted from [12]).

3.3 AMO Algorithm

Adaptive Multiple-Objective (AMO) is a method that incorporates the Kriging and the MOGA. The AMO creates a collection of available samples or uses an available collection in order to approach the problem better than passive searching. This method only rates the designing points when it's necessary. One part of the population can be simulated by rating the Kriging response surfaces. Kriging error prediction, therefore, decreases the amount of necessary evaluations used in finding Pareto peripheral solutions. The AMO flowchart is shown in the second chart in Figure 5.

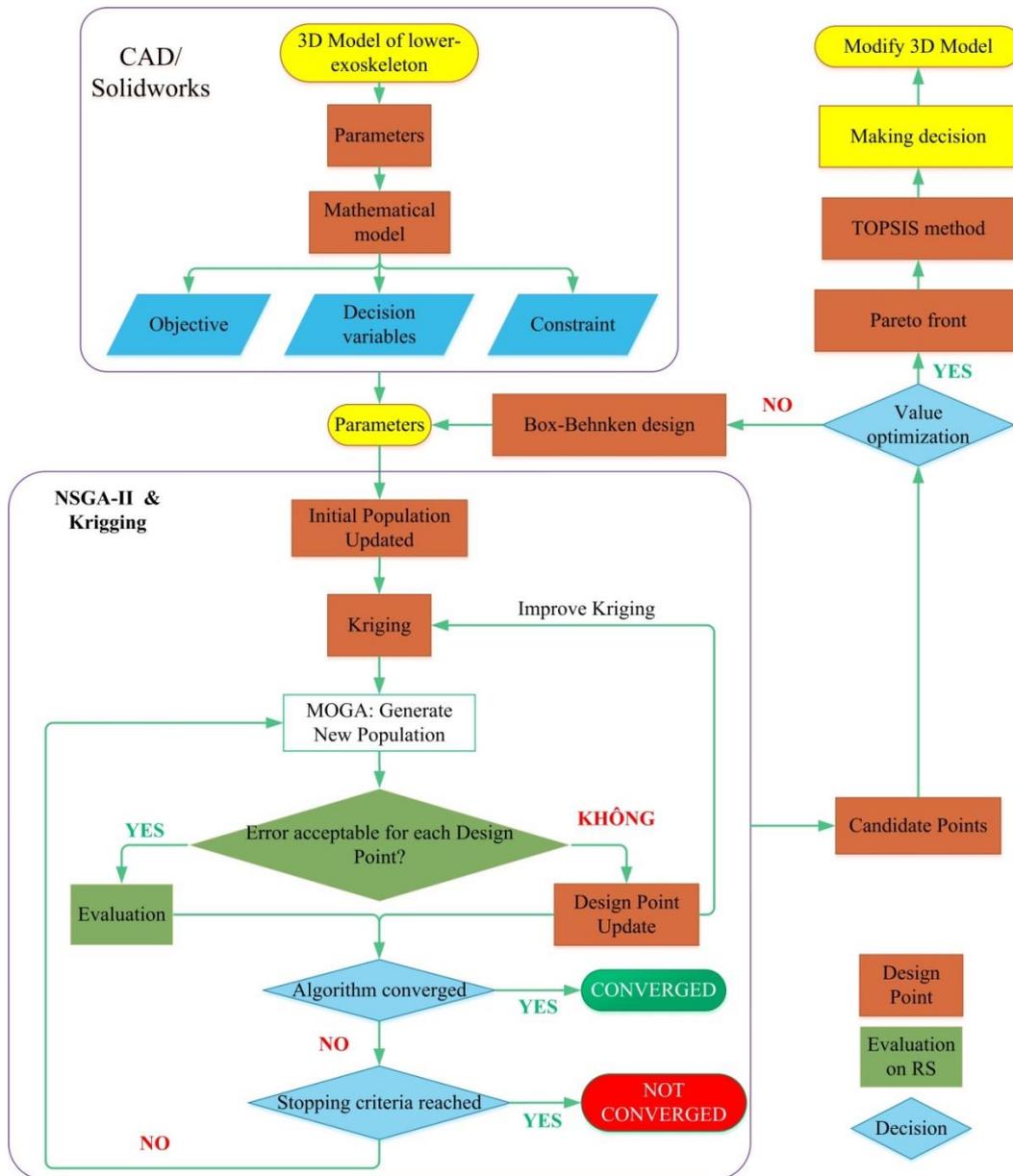


Figure 5. AMO flowchart as general procedure of proposed research method.

3.4 TOPSIS method

TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method was developed in 1981 [13]. It is the decision making method used as there are multiple factors affecting the problem. The chosen decision has the shortest distance to the positive ideal solution and furthest distance to the negative ideal solution. TOPSIS is especially suitable in solving multi-criteria decision making problems.

3.5 Analysis procedures

Based on the model principle, we build the CAD (computer aided design) model in Solidworks and create the basic constraints in the 2D design environment. Then, the target variables are assigned, decision variables and constraining variables according to their attributes that can be connected using Solidworks and ANSYS. In ANSYS, we start running the AMO method using Box-Behnken design technique with three factors as shown in Table 3. From the designed experiments, we begin analyzing

response surfaces to find out the optimum parameters for the AMO method. Moreover, we replace the AMO's default parameters with the ones that we found to get the optimum values for the lower extremity. The results highlighted that the Pareto chart with optimum values was obtained. Finally, we use TOPSIS decision-making method to select the best value from the feasible ones to use in the CAD model. The research procedure is proposed in Figure 5.

Table 3. Factors and their values.

Factors	Levels		
	Highest (1)	Lowest(-1)	Base (0)
Initial samples	1000	500	750
Maximum samples for each generation	300	100	200
Maximum number of generations	100	50	75

4. Results and discussion

The adaptive multiple objectives (AMO) algorithm implemented the calculation process to find the most feasible solutions. After the number of iterations and the terminated condition obtained, ten most solutions were collected based on the non-dominated sorting procedure from the AMO. These solutions as the non-dominated individuals of evolutionary algorithm were shown in Table 4. Then, the TOPSIS was used to determine the score of ranking of the individual's alternatives based on the multiple criteria of sitting points. Table 5 was the experimental plan for determine the optimal parameters of MOGA and AMO algorithms. The data of Table 5 were created based on the simulation of AMO in the ANSYS environment. The design of experiments (DOE) was used to identify the optimal parameters of the number of iteration, number of samples for the MOGA and AMO as Figure 6. Finally we have run the AMO algorithms with above optimal parameters again, we had got 10 individuals that have optimal values and had been described on Pareto frontier in Figure 7. Based on the results obtained in the mentioned 10 individuals, we continued to perform the TOPSIS to choose the best alternative again. In the similar manner with above procedure, we used the MOGA method to identify the optimum results for the best solutions. The results showed that we determined 10 optimum individuals and were presented in the Pareto chart as Figure 8. For the speed of calculation, the AMO showed that the converging results after performing the analysis $n_{AMO} = 1179$ times, and MOGA converges after performing $n_{MOGA} = 1778$ times. Thus, we concluded $n_{AMO}/n_{MOGA} = 1179/1778 = 0.66$, the AMO converged quicker than MOGA algorithm. The connection and interface between the Solidworks (computer aid design system) and ANSYS (computer aided engineering system) to perform the algorithm also played a role to slow down the computational speed. The time needed to switch between the two program needs averagely 15 seconds, so the total time needed to do 15 experiments is quite long and required to be really considered careful at the beginning of the computational process.

Table 4. The 10 optimum individuals after AMO analysis.

Individuals	α	α	α	TOPSIS score	Rank
	Lowest sitting point (α ngoi thap nhat)	Highest sitting point (α ngoi cao nhat)	Standing point (α dung)		
1	24.82	115.08	177.21	0.913	1
2	26.00	97.89	175.72	0.842	2
3	62.34	114.39	179.88	0.578	7
4	19.44	111.12	156.61	0.563	8
5	31.04	88.64	186.42	0.756	3
6	30.96	88.65	186.75	0.751	4
7	30.96	88.65	186.75	0.751	6
8	72.51	119.96	194.40	0.356	10
9	28.28	87.94	190.05	0.716	6
10	24.11	104.13	149.20	0.466	9

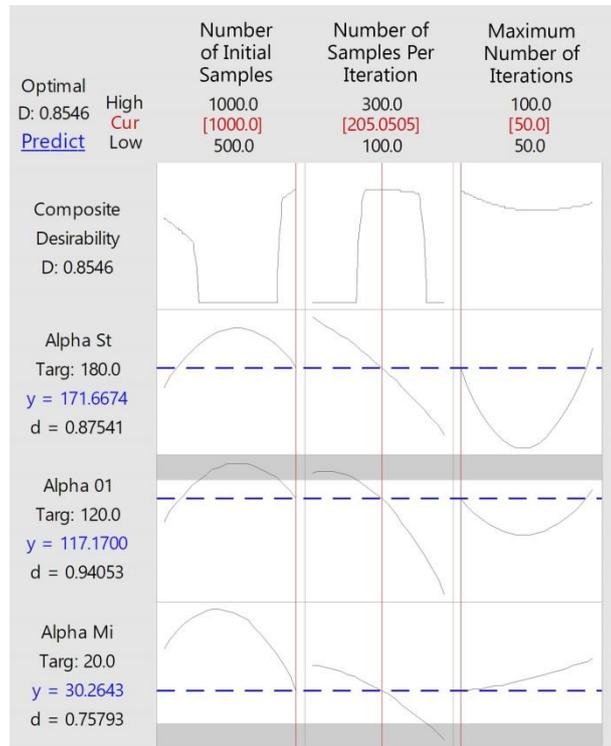


Figure 6. Computation for optimum inputs of AMO method.

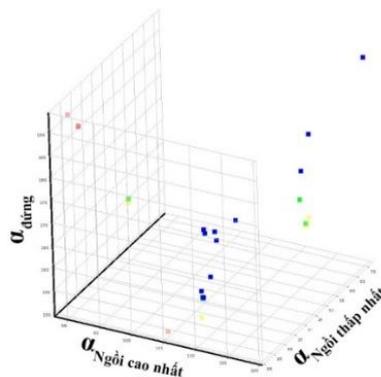


Figure 7. Pareto chart of AMO method.

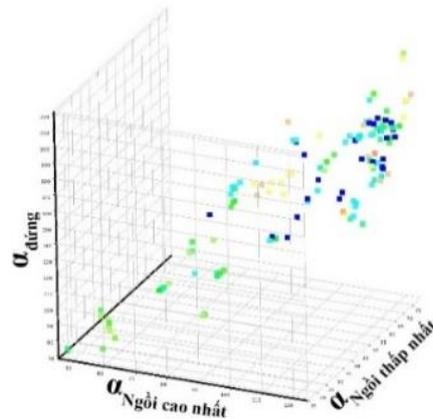


Figure 8. Pareto chart of MOGA method.

Table 5. Results of the experiments.

No	X1	X2	X3	α	α	α
	Beginning samples	Maximum samples for each generation	Maximum number of generations	Lowest sitting point	Highest sitting point	Standing point
1	500	100	75	27.086	72.411	113.121
2	1000	100	75	37.289	110.219	172.925
3	750	100	50	62.403	120.866	176.376
4	750	100	100	62.403	120.866	176.376
5	1000	200	100	34.866	115.048	159.849
6	500	200	50	54.064	116.230	183.107
7	1000	200	50	34.866	115.048	159.849
8	500	200	100	54.064	116.230	183.107
9	750	200	75	59.002	117.364	163.735
10	750	200	75	59.002	117.364	163.735
11	750	200	75	59.002	117.364	163.735
12	1000	300	75	26.231	102.432	167.563
13	500	300	75	35.802	115.835	160.059
14	750	300	100	60.061	119.818	184.290
15	750	300	50	37.289	110.219	172.925

5. Conclusion

The exoskeleton can squat at the lowest knee angle of 24.82°, highest at 115.08° and when not affecting the mobility of the user at 177°. These angles have been suitable with collected data and competitive when compared to the parameters in the market. These values are useful for mechanical design of the lower extremity of the exoskeleton that helps the body to squat or crouch. Besides, we can consider another aspect about the applications of interface between CAD and CAE systems. Especially in this study, the AMO method has shown its advantages over MOGA method in regards of both results and converging time, and the main contributions of this work were determined as follows:

- Built a process that helps optimize multiple objective problems using NSGA-II combined with Kriging.
- Compared MOGA and AMO algorithms.
- Employed the design of experiments to investigate the input factors affecting AMO method.
- Based on the input values and the optimization algorithm, the problem of designing the lower extremity of the exoskeleton was solved.

The advantage of AMO is solving the multiple-objective problem with a faster time of converging. However, because the CAD system has not implemented AMO yet, connecting the two programs prolongs the amount of time needed to calculate and exchange. Changing the parameters only takes 1 or 2 seconds, but switching between two programs takes upwards 13 seconds. Future directions for this research can be implementation of AMO directly integrated into a CAD system such as Solidworks, Autodesk Inventor and Solid Edge. At that time, the computation time can be reduced 10 times for multi-objective design problems compared with the current status.

References

- [1] Mosher R 1967 Handyman to Hardiman SAE Technical Paper 670088
- [2] Dollar AM and Herr H 2008 *IEEE Trans Robot* Vol 24
- [3] Nguyen AT 2015 VNU Journal of Social Sciences and Humanities Vol 1 (1) (in Vietnamese).
- [4] suitX 2017 source: <http://www.suitx.com/legx>, (accessed on 27/12/2017)
- [5] Y. Sankai 2011 "HAL: Hybrid Assistive Limb Based on Cybernetics," Robotics Research: The 13th International Symposium ISRR 25-34
- [6] Noonee 2017 source: <http://www.noonee.com/>, (accessed on 27/12/2017)
- [7] Archelis 2017 source: <https://www.archelis.com/>, (accessed on 27/12/2017)
- [8] Bruno S and Oussama K 2008 *Springer Handbook of Robotics*, Springer-Verlag Berlin Heidelberg, ISSN: 978-3-540-30301-5, DOI: 10.1007/978-3-540-30301-5 p 773-793
- [9] Valiente A 2005 Massachusetts Inst of Tech Cambridge Media Lab
- [10] Mukhtar A, Ng K C and Yusoff M Z 2017 *Int J Model Optim* Vol 7 p 92-97
- [11] Deb K, Pratap A, Agarwal S and Meyarivan T 2002 *IEEE Transactions on Evolutionary Computation* Vol 6 No 2 p 182-197
- [12] ANSYS Help 2017 <https://www.ansys.com>, accessed on 27/12/2017
- [13] Lokare VT and Jadhav PM 2016 " IEEE Proc. 2016 Int. Conf. on Computer Communication and Informatics (ICCCI, 7-9 Jan. 2016) Coimbatore India p 1-6