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Exploring Neural Network to Predict Car Tyre Inflation Time and Power Requirement of a Tyre Pressure Control Unit.

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Exploring Neural Network to Predict Car Tyre Inflation Time and Power Requirement of a Tyre Pressure Control Unit.

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Abstract
This study used Artificial Neural Network (ANN) for the prediction of power required to inflate different tyre sizes and inflation times. ANN is a widely accepted machine learning method that uses past data to predict future trend. An existing database obtained experimentally from a tyre pressure control test rig was optimized using genetic algorithm(GA) which is an optimization tool that can find better subsets of input variables for importing into ANN. The ANN results were compared with the results obtained experimentally. The results show that the model can be implemented in modern day tyre pressure control designs and be used to predict inflation times and power required to inflate different tyre sizes.
Keywords: Predictive, Algorithm, Neural, Network, Inflation, Power, Time, Pressure, Genetic.

1. Introduction
Genetic algorithm (GA) is an optimization device with source from evolution theory [1]. A traditional genetic algorithm tries to find an optimum of a cost function which does not change during the optimization process. Although genetic algorithm can be used to imitate the natural environment of a system, it cannot be used for decision mechanism. The utilization of artificial intelligence techniques in tyre and tyre pressure control system designs is a recent development.

2. Literature Review
Artificial Neural Networks (ANNs) are attractive for the classification of remotely sensed data. However, a wide range of factors influence the accuracy with which a data may be classified. [2]. Some past researchers in tyre and tyre pressure control systems proposed related works using Genetic Algorithm and Neural Networks. For example, ANN based method was projected for tyre/road friction estimation [3] for the forecasting of tyre handling efficiency [5, 7] and for modeling rate of tyre failure [4]. Luca and Stefano (2011) developed and applied fuzzy control algorithm optimization for tyre burst.[6] also developed an Al-Based model to determine vehicle tyre design configuration. [7] investigated and optimized the variables for the design of tyre using finite element analysis and correlation with performance. [8] proposed a Neural Network based fault diagnosis for non-linear dynamic system.

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3. Methodology

3.1 Data Preparation

The ANN method was developed to use existing experimental database obtained from tyre pressure control test rig constructed. The inflation times, tyre sizes and nominal pressures are the primary input parameters. Figure 2 depicts the algorithm flow chart proposed in this work. A single objective GA function approximation was used to generate more data from the imported data because of the non-continuous nature of the inflation pressure.

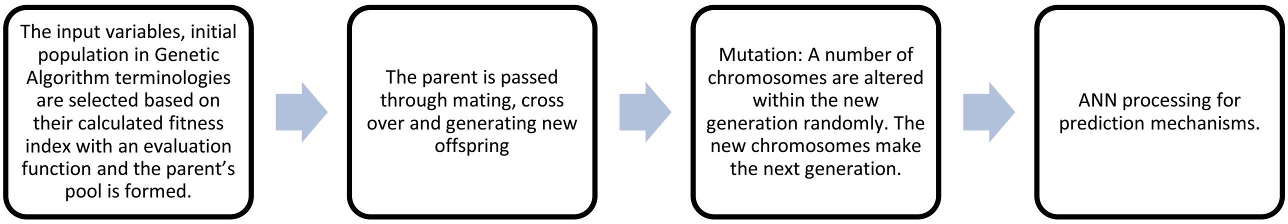

Figure 1: Algorithm Flow Chart

3.2 Data Processing

The procedure used to develop the neural network model for this work is similar to that used by [9] to develop an adequate technique with neural network to predict car tyre micro-scale and macro-scale behaviour. Luca and Stefano (2011) developed and applied fuzzy control algorithm optimization for tyre burst [11]. The neural method was developed to use experimental inflation times, nominal pressure and tyre sizes as the primary inputs. In these simulations, (GA) function approximations were used to generate more data from the experimental results obtained because of the non-continuous nature of the inflation pressure. GA optimization algorithm changes the number of neurons in hidden layer(s) and obtains an optimized structure in terms of accuracy and efficiency. The number of neurons was determined based on closer correlation of networks output with desired values. This algorithm imitates natural evolution process of the pressure control system using the imported data as the input variables. After creating the initial population, P, individual iteration, was made to pass through crossover and mutation. The fitness value, v of each of the iterations was then calculated and selection of individuals for the new generation took place. This algorithm is as follows:

Step 1:

Initialize population P (P_{io}*, dP_i* , t_i*).

Step2

Generate p trees at random, for each tree:– Randomly generating a rooted tree with ordered branches.

Step 3

Randomly select functions from function set to be root. e.g (+,-,*,/, sin,cos,tan,ln,e,).

Step 4

Create Z(f) children; each function has Z(f) arguments.

Step 5

Repeat recursively until tree is completely labeled with terminal as leaves.

Step 6

Evaluate: For each v in P, compute Fitness(v)While **[maxFitness(v)]<Fitnessthresholddo.**

Step 7

Create a new generation Ps.

Step 8
Crossover: applying the Crossover operator. Add all offspring to Ps.
Step 9
Mutate: Choose m percent of the members of P with uniform probability. For each, replace a subtree by a randomly generated new tree.
Step 10
Update P with Ps.
Step 11
Evaluate: for each v in P, compute Fitness (v).
Return the hypothesis (function) from P that has the highest fitness.
Accurate and efficient optimized structure was obtained by genetic optimization algorithm by changing the quantity of neutrons in hidden layer(s). The training samples depicted closer correlation factors. ANN output results showed the accurate prediction of new samples. ANN output results showed the accurate prediction of new samples. Elapsed time for training was also used to evaluate the network efficiency in the training session. Comparisons of the results were based on correlation factor, training effort and their network performance when engaging new data [10].

3. Results and Discussion

Table 1 summarizes the simulated results obtained for inflation time and power required by tyre pressure control system for different tyre sizes and nominal pressures. it can be deduced from the table below that the developed model showed that power required in watt to inflate a pneumatic tyre increases as the inflation time increases. The simulated and experimental results obtained were as tabulated below. The results showed that there is a correlation between the experimental results obtained for tyre size R16 in previous work (see appendix) and the results obtained through this model.

Table 1 : Simulated results for Tyre Sizes R16, R15, R14 and R12

	R16(Experimental)		**R15(Simulated)**		**R14(Simulated)**		**R12(Simulated)**	
S/N	**t secs**	**E joules**	**t secs**	**E joules**	**t secs**	**E joules**	**t secs**	**E joules**
1	41.00	13.8765	37.14	12.2562	34.16	11.2728	31.02	10.2366
2	85.00	27.66	79.36	26.1888	75.22	24.8225	73.15	24.1395
3	126.00	41.98	121.25	40.0125	119.24	39.3492	115.24	38.0292
4	170.00	57.01	168.99	55.7667	164.33	54.2289	160.11	52.8363
5	209.00	69.05	201.13	66.3729	198.25	65.4225	195.57	64.5381
6	252.11	84.388	248.05	81.8565	245.31	80.9523	241.35	79.6455
7	293.00	99.02	289.01	95.3733	281.11	92.7663	319.25	91.8489
8	339.13	113.05	331.11	109.2663	327.28	108.0024	319.25	105.3525
9	378.15	126.50	355.44	117.2952	349.19	115.2327	342.48	113.0184
10	423.00	142.83	398.21	131.4093	382.15	126.1095	378.31	124.8423
11	431.00	142.83	401.14	132.3762	398.17	131.3961	390.14	128.7462

Figure 2 shows the simulated graph at 0 and 0.35 bar nominal and change in inflation pressure for tyre size R16 in static position.
Figure 3 shows the simulated graph at 0 and 0.70 bar nominal and change in inflation pressure for tyre size R16 in static position.

Figure 4 shows the simulated graph at 0 and 1.05 bar nominal and change in inflation pressure for tyre size R16 in static position.
Figure 5 shows the simulated graph at 0 and 1.40 bar nominal and change in inflation pressure for tyre size R16 in static position.
Figure 6 shows the simulated graph at 0 and 1.75 bar nominal and change in inflation pressure for tyre size R16 in static position.
Figure 7 shows the simulated graph at 0 and 2.10 bar nominal and change in inflation pressure for tyre size R16 in static position.
Figure 8 shows the simulated graph at 0 and 2.45 bar nominal and change in inflation pressure for tyre size R16 in static position.
Figure 9 shows the simulated graph at 0 and 2.80 bar nominal and change in inflation pressure for tyre size R16 in static position.

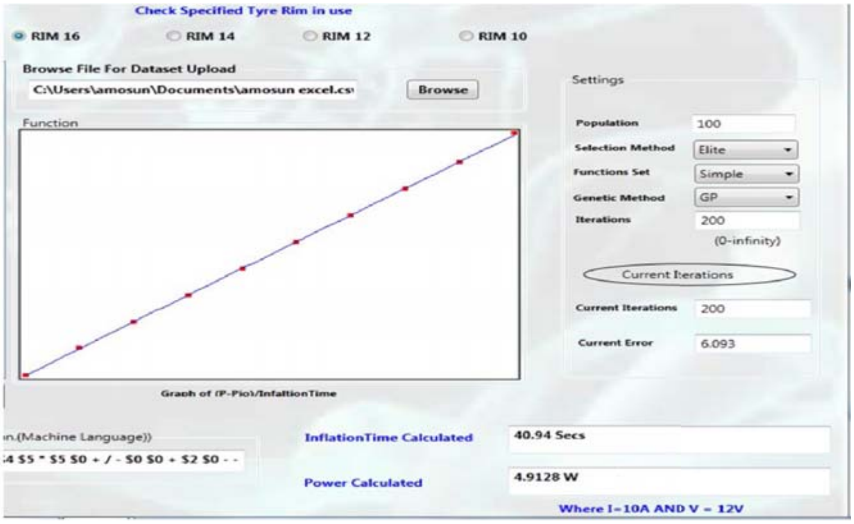

Figure 2: Training graph of training dataset.

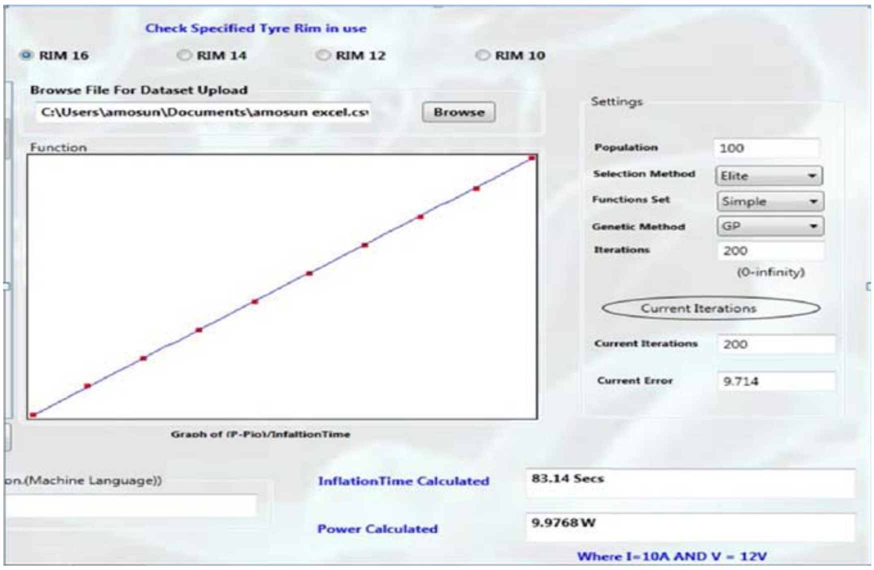

Figure 3: Simulation graph at 0 an

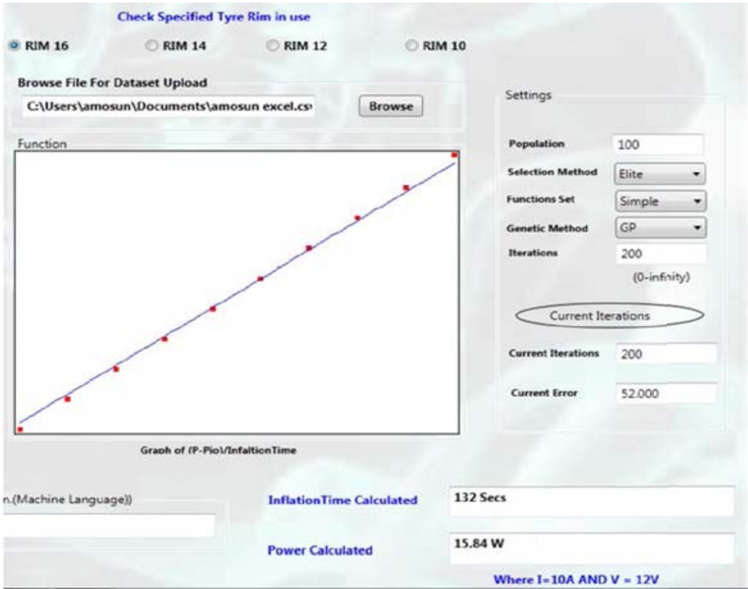

Figure 4 : Simulation graph at 0 and 1.05bar nominal and change in inflation pressures (static)

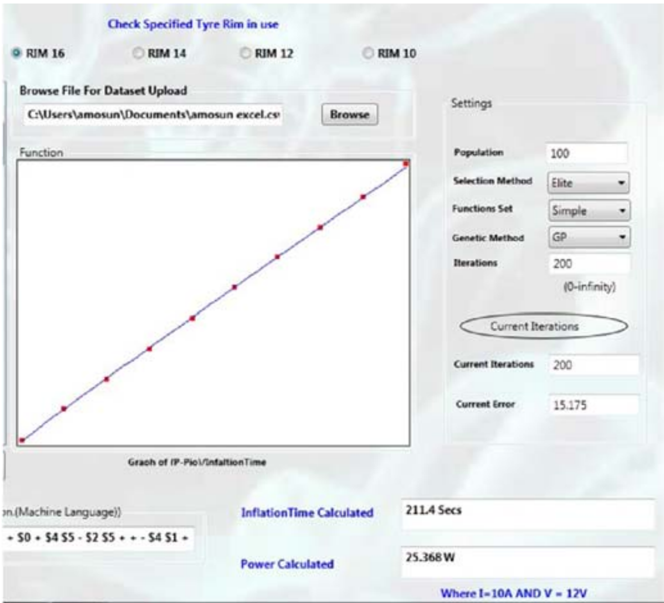

Figure 5 : Simulation graph at 0 and 1.40 bar nominal and change in inflation pressures (static)

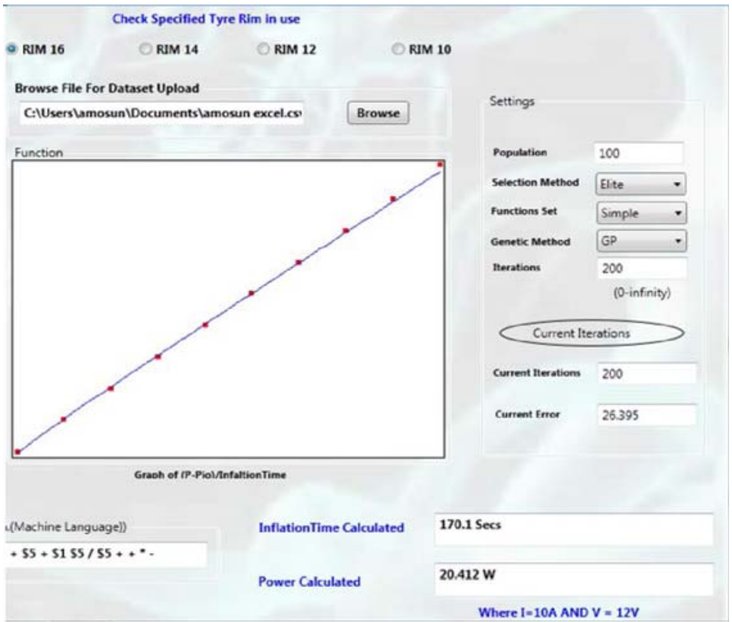

Figure 6 : Simulation graph at 0 and 1.75bar nominal and change in inflation pressures (static)

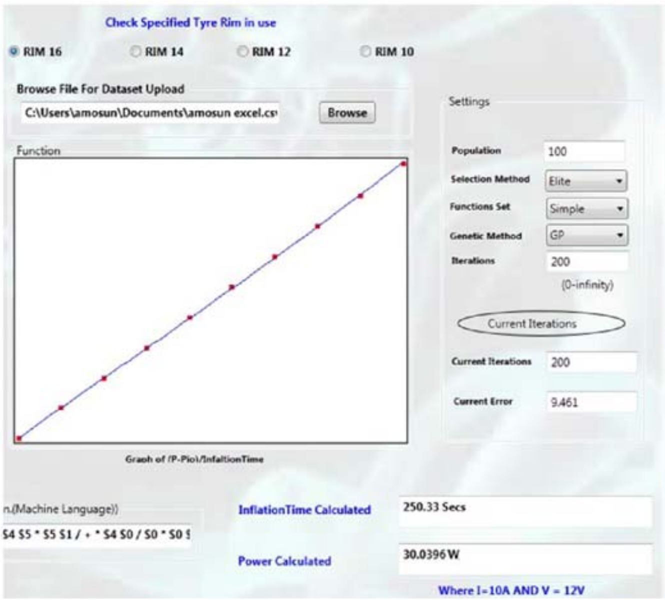

Figure 7 : Simulation graph at 0 and 2.10bar nominal and change in inflation pressures (static)

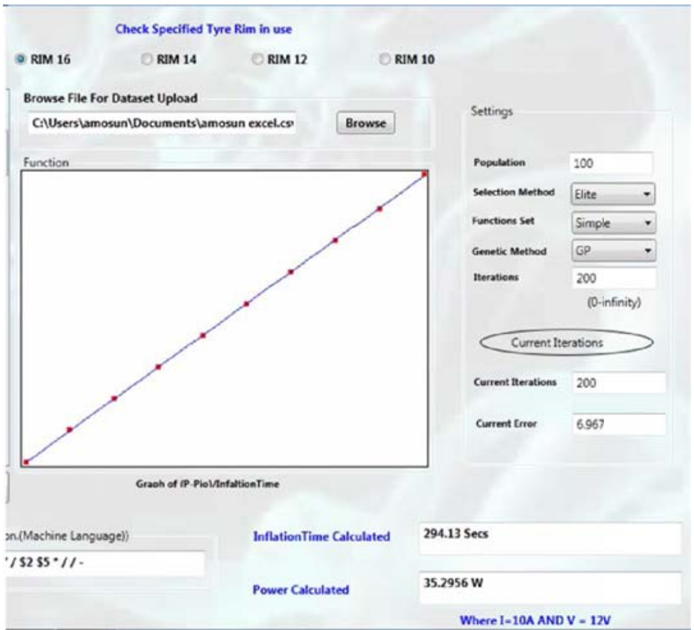

Figure 8 : Simulation graph at 0 and 2.45bar nominal and change in inflation pressures (static)

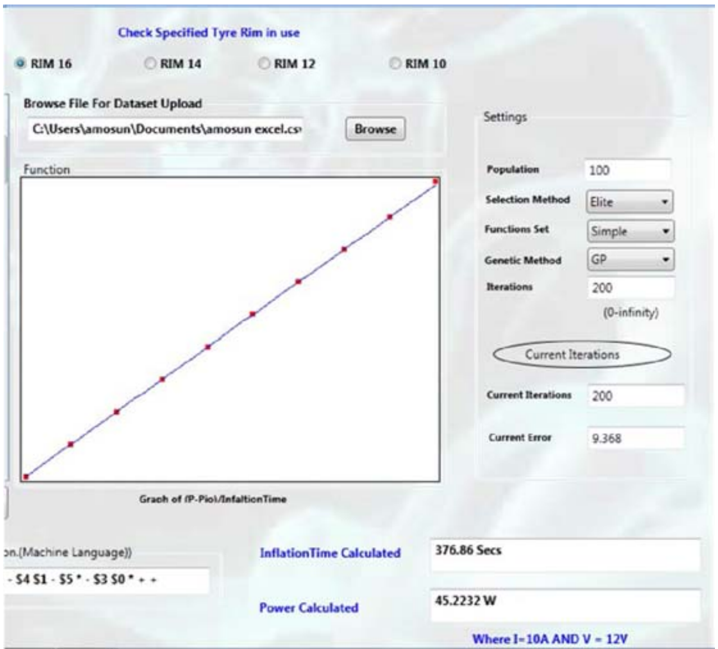

Figure 9 : Simulation graph at 0 and 2.80bar nominal and change in inflation pressures (static)

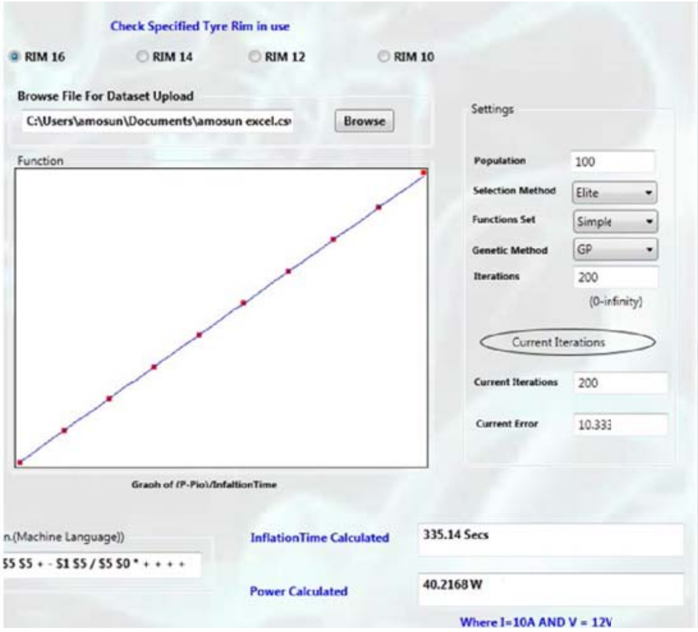

Figure 10 : Simulation graph at 0 and 3.15bar nominal and change in inflation pressures (static)

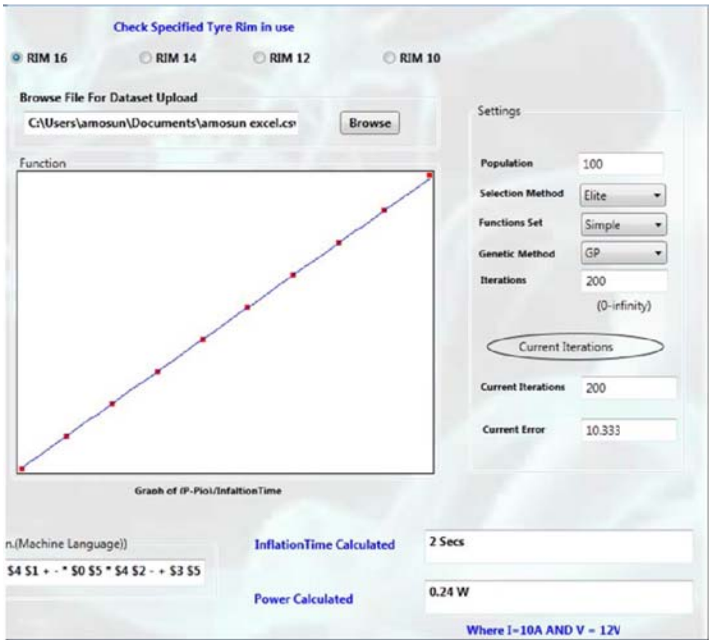

Figure 11 : Simulation graph at 0 and 3.50 bar nominal and change in inflation pressure (dynamic)

Figure 10 shows the simulated graph at 0 and 3.15 bar nominal and change in inflation pressure for tyre size R16 in static position.
Figure 11 shows the simulated graph at 0 and 3.50 bar nominal and change in inflation pressure for tyre size R16 in static position.

3. Conclusion

So far a predictive model for tyre pressure control system has been proposed with emphasis on power and inflation times. Using various equations and soft wares, new algorithm for the prediction of power requirements and inflation times calculation during design of tyre pressure control system has been discussed. First of all genetic algorithm was used to imitate the natural environment of the pressure control system. Then using neural network as our predictive mechanism, our model could predict power requirements and inflation times when designing tyre pressure control system. The simulated results obtained can be used to predict inflation times and power requirements for different tyre sizes which will help tyre pressure control system designers to achieve an optimized design quickly.

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APPENDIX

Table 2 : Static and dynamic experimental results at 0 nominal pressure.

	Static			Dynamics		
P_{io} (bar)	dP_s (bar)	t_s (secs)	W_s (Joules)	dP_d (bar)	t_d (secs)	W_d (bar)
0	0.35	42	14	0.35	33	11
0	0.70	85	28	0.70	61	20
0	1.05	126	42	1.05	90	30
0	1.40	168	56	1.40	122	41
0	1.75	210	70	1.75	151	50
0	2.10	252	84	2.10	183	61
0	2.45	294	98	2.45	211	70
0	2.80	336	112	2.80	240	80
0	3.15	378	126	3.15	275	92
0	3.50	423	141	3.50	302	101