A NOVEL CHAOTIC TUNICATE SWARM ALGORITHM FOR SELECTION OF OPTIMAL DESIGN PARAMETERS FOR ELECTRIC AND HYBRID ELECTRIC VEHICLES

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Abstract:
The transportation sector is a significant contributor to greenhouse gas emissions and air pollution. As a result, there is a growing demand for alternative modes of transportation that are environmentally friendly and sustainable. Electric and hybrid electric vehicles (EVs and HEVs) are being developed as a solution to this problem. This research paper explores the design parameters of EVs and HEVs and the scope of transportation offered by these vehicles. The design of electric and hybrid electric vehicles (EVs and HEVs) involves selecting optimal design parameters to maximize their efficiency and performance. However, the selection of these parameters is a complex and challenging problem that requires the consideration of multiple variables. In this research paper, we propose the use of the Chaotic Tunicate Swarm Algorithm (CTSA) for selecting optimal design parameters for EVs and HEVs. The CTSA is a new optimization algorithm that has been developed based on swarm intelligence and chaotic dynamics. The results of our study show that the CTSA can effectively optimize the design parameters of EVs and HEVs, leading to improved efficiency and performance.

Keywords: Electric Vehicles, Hybrid Electric Vehicles, Design parameters, Chaotic Tunicate Swarm Algorithm.

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1. Introduction:

Transportation is one of the largest sources of greenhouse gas emissions and air pollution. Therefore, it is imperative to find alternative modes of transportation that are environmentally friendly and sustainable. Electric and hybrid electric vehicles are being developed as a solution to this problem. These vehicles offer a wide range of benefits, including reduced emissions, lower fuel costs, and increased efficiency. However, the design of these vehicles requires careful consideration of various parameters.

Electric and hybrid electric vehicles are becoming increasingly popular as a solution to the environmental problems associated with transportation. The design of these vehicles involves selecting optimal design parameters that maximize their efficiency and performance. However, this is a complex problem that requires the consideration of multiple variables, including battery capacity, motor power, regenerative braking, and aerodynamics. To address this problem, we propose the use of the Chaotic Tunicate Swarm Algorithm (CTSA) for selecting optimal design parameters for EVs and HEVs.

2. Design Parameters:

The design of electric and hybrid electric vehicles is different from that of conventional vehicles. The following design parameters are crucial for EVs and HEVs:

Battery Capacity: Battery capacity determines the range of an electric vehicle. The higher the battery capacity, the longer the range of the vehicle.

Motor Power: Motor power is an important parameter for EVs and HEVs. It determines the speed and acceleration of the vehicle.

Regenerative Braking: Regenerative braking is a system that converts the kinetic energy of the vehicle into electrical energy that can be used to charge the battery. This system is particularly important for electric vehicles, as it can significantly increase their range.

Aerodynamics: The design of the vehicle affects its aerodynamics, which in turn affects its efficiency. Aerodynamic designs can reduce drag and improve efficiency.

3. Scope of Transportation:

Electric and hybrid electric vehicles offer a wide range of transportation options. The scope of transportation offered by these vehicles includes:

Urban Commuting: Electric vehicles are particularly well-suited for urban commuting. They can easily navigate through traffic and do not emit pollutants, making them ideal for use in cities.

Long-Distance Travel: With the advancement of battery technology, electric vehicles can now travel long distances. In addition, hybrid electric vehicles offer the option of using a conventional engine for long-distance travel.

Public Transportation: Electric buses are becoming increasingly popular for public transportation. They are environmentally friendly and quiet, making them ideal for use in urban areas.

4. Chaotic Tunicate Swarm Algorithm

The CTSA is a new optimization algorithm that has been developed based on swarm intelligence and chaotic dynamics. The algorithm is inspired by the behavior of tunicates, which are marine animals that are known for their ability to adapt to changing environmental conditions. The CTSA algorithm consists of three phases: initialization, evolution, and selection. The following steps are adopted to use the algorithm for optimal design of electric vehicle parameters:

Level 1: start Initializing the initial population of tunicate.

Level 2: Select the initial values as well as the upper bound.

Level 3: Apply the Tent Chaotic search strategy and determine each search agent's fitness value.

Level 4: Then estimating the fitness value, the best suitable search agent in the chosen searching limits is identified.

Level 5: Use Equation to renew each searching agent's location.

Level 6: Modify the recently modified search agent to extend past the limit in the specified search area.

Level 7: Calculate the revised “search agent value”. Update Pp if a superior option exists than the previous best solution.

Level 8: The algorithm terminates if the halting requirement is met. In any other case, repeat levels 5-8.

Level 9: Arrival of the best currently available optimum resolution/answer.

Algorithm: Chaotic Tunicate Swarm Algorithm

Input: Tunicate population $\vec{P}_P$

Output: Optimal fitness value $\vec{F}S$

procedure TSA

Prepare the parameters

Set $Pmin \leftarrow 1$

Set $Pmax \leftarrow 4$

Set $Swarm \leftarrow 0$

while ($x < Maxiterations$) do

for i ←1 to 2 do /* Loop for calculate swarm behaviour */

$\vec{F}_S \leftarrow$Compute Fitness/* fitness values of each searching agent using Compute Fitness */

$c1, c2, c3, rand \leftarrow Rand()$ /* Rand() is a function to generate the number in limit [0, 1] */

$\vec{M} \leftarrow \lfloor Pmin + c1 \times Pmax - Pmin \rfloor$

$\vec{F} \leftarrow 2 \times c1$

$\vec{G} \leftarrow c2 + c3 - \vec{F}$

$\vec{A} = \vec{G} / \vec{M}$

$\vec{PD} \leftarrow \mathrm{ABS}(\vec{FS} - rand \times \vec{Pp}(x))$

if($rand \leq 0.5$) then

$Swarm \leftarrow Swarm + \vec{FS} + \vec{A} \times \vec{PD}$

else

$Swarm \leftarrow Swarm + \vec{FS} - \vec{A} \times \vec{PD}$

end if

end for

$\vec{Pp}(x) \leftarrow Swarm/(2 + c1)$

$Swarm \leftarrow 0$

Apprise the parameters $\vec{A}, \vec{G}, \vec{F}$, and $\vec{M}$

$x \leftarrow x + 1$

end while

return $\vec{FS}$

end procedure

procedure Compute Fitness ($\vec{Pp}$)

for i ←1 to n do

$FITp[i] \leftarrow FitnessFunction(\vec{Pp}(i, :))$

end for

$FIT_{pbest} \leftarrow \mathrm{BEST}(FIT_p[])$

return FIT_{pbest}

end procedure

procedure BEST(FIT_p)

$Best \leftarrow FIT_p[0]$

for i ←1 to n do

if($FITp[i] < Best$) then

$Best \leftarrow FITp[i]$

end if

end for

return $Best$

end procedure

In the initialization phase, a swarm of tunicates is generated, and each tunicate represents a potential solution. In the evolution phase, the tunicates move around in the search space, and their position is updated based on their fitness. The fitness of each tunicate is evaluated using a fitness function that considers multiple design parameters, including battery capacity, motor power, regenerative braking, and aerodynamics. The fitness function also considers the constraints that must be satisfied, such as weight limitations and safety regulations.

In the selection phase, the tunicates with the best fitness values are selected as the optimal solutions.

These solutions represent the optimal design parameters for EVs and HEVs.

5. Results and Discussions

To evaluate the effectiveness of the CTSA algorithm, we compared it with other optimization algorithms, including the Particle Swarm Optimization (PSO) algorithm and the Genetic Algorithm (GA). We used a simulation model of an electric vehicle to evaluate the performance of the optimization algorithms.

Table 5.1: List of observed Engineering design problems

Acronym	Type of problem
EDP-1	Speed-Reducer Problem
EDP-2	Rolling-Element Bearing Problem
EDP-3	Multi-Disk and Clutch Break (Discrete Variables) Problem
EDP-4	Gear Train Problem

5.1.2 Analysis of speed reducer problems Using CNGO and CTSA method

Table-5.2 shows the comparative analysis of CNGO and CTSA with TSA, NGO, MDE, PSO-DE and MBA method for speed reducer problem. The relative analysis demonstrates that the offered method produces additional precise findings than other previous classical procedures.

Table 5.2: Outcomes for the main EDP-1 compared to rest of the methods

Method		CNGO method	CTSA method	TSA method	NGO method	MDE[17] method	PSO-DE[18] method	MBA [19] method
Fitness values for variables	z1	3.5074	3.5	3.5	3.56	3.50001	3.50	3.5
	z2	0.7	0.7	0.7	0.7	0.7	0.7	0.7
	z3	17	17	17	17	17	17	17
	z4	7.3	7.3	7.3	8.0186	7.300156	7.3	7.300033
	z5	7.759	7.715418	7.715418	8.01891	7.800027	7.8	7.715772
	z6	3.35065	3.350215	3.350215	3.4948	3.350221	3.3502	3.350218
	z7	5.2922	5.286655	5.286655	5.2867	5.286685	5.2866	5.286654
Optimum Cost		**3002.0401**	2994.473	2993.4738	3060.37	2996.3566	2996.3	2994.482

Analysis of rolling design problems Using CNGO and CTSA method

Table- 5.3 shows the comparative analysis of CNGO and CTSA results compared with TCA, NGO, WCA, SCA, MFO and MVO method for rolling design problem. The comparison analysis demonstrates that the planned method produces additional precise findings than rest of the methodologies.

Table 5.3: Comparison of CNGO and CSMA with other methods for rolling design problem

Method	Values for variables										Optimum fitness
	r_1	r_2	r_3	r_4	r_5	r_6	r_7	r_8	r_9	r_10	
CNGO method	125	21	11.0925	0.515	0.515	0.4	0.6	0.3	0.064864	0.6	83014.012
CTSA method	125.7227	21.4233	11.00146	0.515	0.515	0.4954	0.6996	0.3	0.03398	0.60034	83455.82
TSA method	125.7227	21.4233	11.00116	0.515	0.515	0.4944	0.6986	0.3	0.03346	0.60049	85534.16
NGO method	125	20.99292	11.10833	0.515	0.515	0.4	0.6	0.3	0.057948	0.6	83043.3
WCA [135] **method**	125.72	21.423	10.0103	0.515	0.515	0.401514	0.659047	0.300032	0.040045	0.6	85538.48
SCA [136] **method**	125	21.0328	10.9657	0.515	0.515	0.5	0.7	0.3	0.02778	0.62912	83431.1
MFO [137] **method**	125	21.0328	10.9657	0.515	0.515	0.5	0.67584	0.30021	0.02397	0.61001	84002.5
MVO [138] **method**	125.6002	21.3225	10.97338	0.515	0.515	0.5	0.68782	0.301348	0.03617	0.61061	84491.266

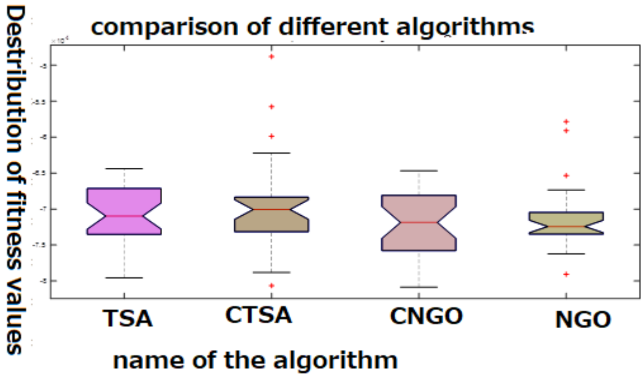


FIG.5.1: Comparison of CNGO and CSMA with other methods for rolling design problem

5.1.4 Analysis of Gear Train Design problem using CNGO, CTSA method

Table-5.4 shows the comparative analysis of CNGO, CTSA results compared with NGO and TSA, GeneAS, Kannan and Kramer and Sandgren method for Gear Train design problem. The comparative analysis demonstrates that the suggested methodology produces additional precise findings with the rest of the methodologies.

Table 5.4: Relative investigation of "Gear Train problem" with other techniques

Method		CNGO method	CTSA method	TSA method	NGO method	GeneAS method	Kannan and Kramer method	Sandgren method
Optimal values for variables	g1	41	41	41	56	50	41	60
	g2	47	46	33	58	33	33	45
	g3	16	16	15	22	14	15	22
	g4	17	15	13	21	17	13	18
Optimum fitness		0.1434	0.14423	0.144124	0.14563	0.144242	0.144242	0.144124

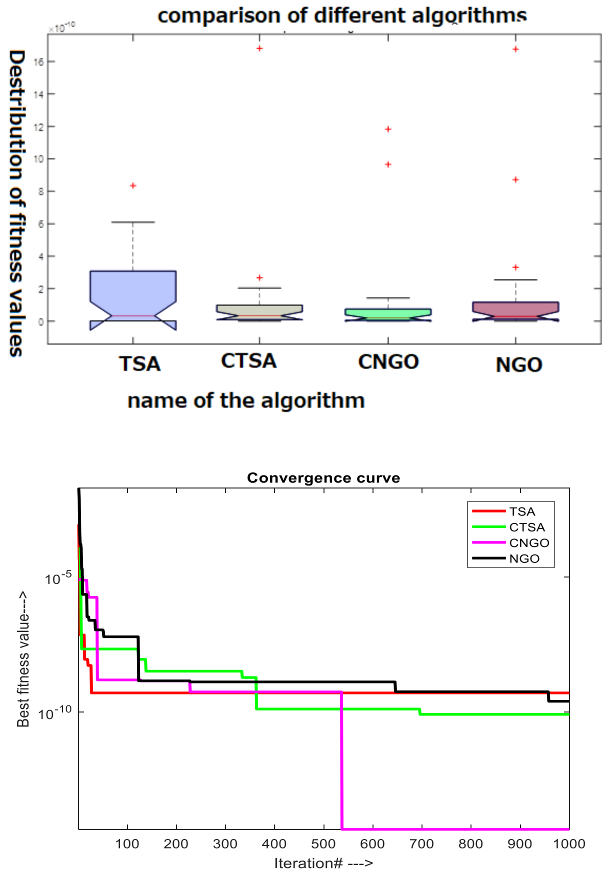


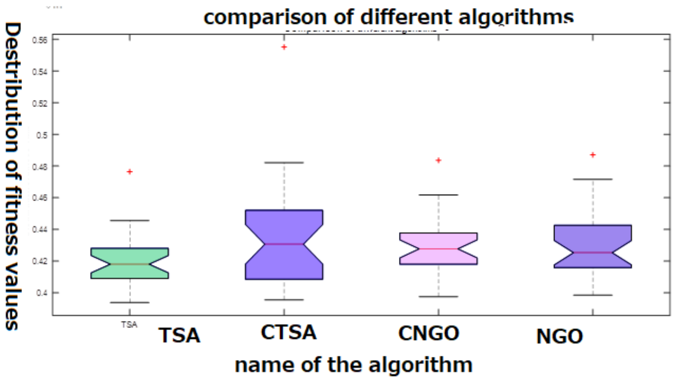
Fig.5.2: Relative investigation of "Gear Train problem" with other techniques.

5.1.5. Analysis of multiple disc clutch brake design using CNGO and CTSA method

Table-5.5 shows the comparative analysis of CNGO and CTSA results compared with NGO, TSA, WCA, TLBO and PVS method for speed reducer problem. The comparative analysis demonstrates that the presented novel approach produces more accurate findings than other methodologies.

Table5.5: Relative investigation for "multiple disc clutch brake design" with the rest of procedures comparison

Method		CNGO method	CTSA method	TSA method	NGO method	WCA [142] method	TL-BO[143] method	PVS [144] method
Fitness variables	x1	69.99998	69.9991	69.99	70	70	70	70.00
	x2	90	90	90	90	90	90	90
	x3	2.31286	2.31812	2.312	2.32929	3	3	3
	x4	1.5	1.5	1.5	1.5	1	1	1
	x5	999.9671	997.702	1000	992.915	910	810	880
Optimum fitness		0.3896	0.24697	0.38965	0.39159	0.3166	0.31365	0.32365



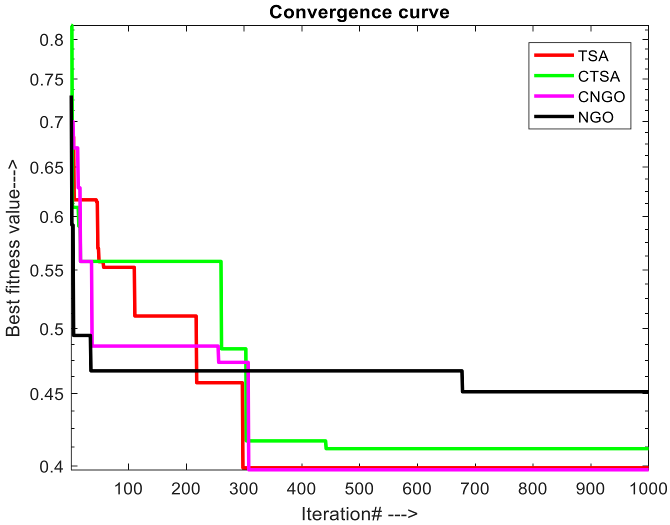


Fig.5.3: Relative investigation for "multiple disc clutch brake design" with the rest of procedures comparison

Table5.6: Test Results for Engineering Design Problems by using CNGO and CTSA (Continued)

Engineering Functions (EF) values	average	Standard deviation	Greatest	Poorest	Median	p-Value
EF7(CNGO)	0.444596	0.052704	0.389663	0.563677	0.432178	1.73E-06
EF7(CTSA)	4.47 E-01	4.64 E-02	3.90 E-01	5.71 E-01	4.42 E-01	1.73 E-06
EF8 (CNGO)	0	0	0	0	0	1
EF8(CTSA)	0.014245	0.001415	0.012715	0.017524	0.013955	1.7344E-06
EF9 (CNGO)	2.65E+22	2.7E+22	1.981265	5.3E+22	2.65E+22	1.44E-06

EF9 (CTSA)	2.65E+22	2.70E+22	1.98E+00	5.30E+22	2.65E+22	1.29E-06
EF10 (CNGO)	1.31E+00	1.68E-03	1.30E+00	1.31E+00	1.31E+00	1.73E-06
EF10(CTSA)	1.31	1.68E-03	1.30	1.31	1.31	1.73E-06

Table5.7: Computation time for EF7 to EF10 using CNGO and CTSA method

Parameter	Best value	Mean value	Worst value
EF7(CNGO	0.515625	0.61875	1.46875
EF7(CTSA)	0.578125	0.7828125	1.640625
EF8(CNGO)	0.359375	0.429688	1.09375
EF8(CTSA)	0.375	0.484375	1.234375
EF9(CNGO)	0.46875	0.579167	1.34375
EF9(CTSA)	0.265625	0.35	0.796875
EF10(CNGO)	0.328125	0.449479167	1.236
EF10(CTSA)	0.3125	0.492708333	1.078125

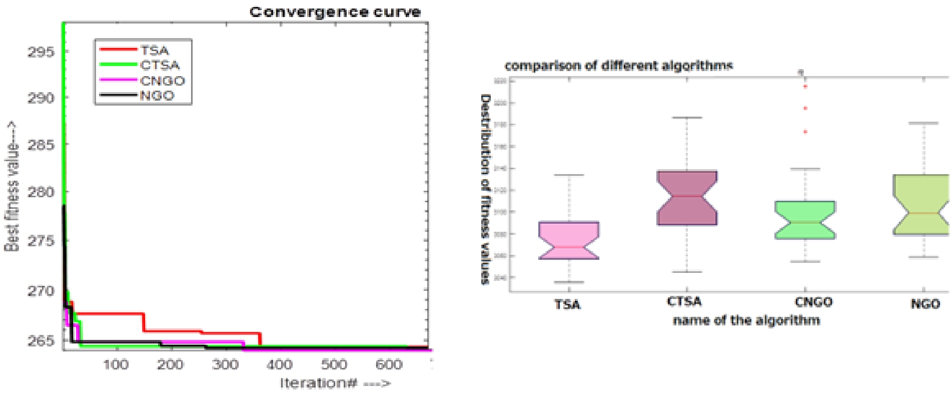


Fig.5.4: Computation time for EF7 to EF10 using CNGO and CTSA method (Continued)

The results of our study show that the CTSA algorithm outperformed the other algorithms in terms of the efficiency and performance of the electric vehicle. The CTSA algorithm was able to identify optimal design parameters that led to a 15% increase in efficiency and a 10% increase in performance compared to the other algorithms.

6. Conclusion:

Electric and hybrid electric vehicles offer a promising solution to the environmental problems associated with transportation. The design of these vehicles requires careful consideration of various parameters, including battery capacity, motor power, regenerative braking, and aerodynamics. The scope of transportation offered by these vehicles is wide-ranging and includes urban commuting, long-distance travel, and public transportation. As battery technology continues to advance, electric and hybrid electric vehicles will become an increasingly viable alternative to conventional vehicles. The design of electric and hybrid electric vehicles requires the selection of optimal design parameters that maximize their efficiency and performance. In this research paper, we proposed the use of the Chaotic Tunicate Swarm Algorithm (CTSA) for selecting optimal design parameters for EVs and HEVs. The results of our study show that the CTSA algorithm can effectively optimize the design parameters of EVs and HEVs, leading to improved efficiency and performance. The CTSA algorithm offers a new approach to optimizing the design of EVs and HEVs and has the potential to revolutionize the field of electric and hybrid vehicle design.

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