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The GA-ANN expert system for mass-model classification of TSTO surrogates

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ABSTRACT

A hybrid-heuristic machine learning methodology, based on hybrid genetic algorithm (GA) and artificial neural network (ANN) data classification methods is proposed as an expert system for assessing viability of surrogates of a two-stage-to-orbit (TSTO) vehicle. The methodology is integral to the inverse design method for spaceplane systems. Since spaceplanes do not exist therefore archival mass-model data is also non-existent and inverse design method is used to generate optimal vehicle configuration data. The GA-ANN offers an expert system whereby when a new vehicle configuration is evolved its mass-model is first optimized using GA and then the optimal solution is processed through the ANN classifier to assess the viability of solution. If classification result fails the process is repeated until a qualified result is obtained. Results are validated using mass-model parameters of HTSM (hypersonic transport system Munich) vehicles.

1. Introduction

Of late surrogates of modular designs for a waverider integrated hypersonic compression system have been proposed [1] and a cognitive-heuristic decision algorithm called DF-APSO [2] was introduced for selection of the most suitable baseline configuration from amongst the surrogates. In 2011 an evolutionary two-step improved PSO (particle swarm optimization) algorithm was proposed [3] and subsequently used for preliminary heuristic optimization of hypersonic compression system [4]. However once the optimal design had been obtained there still remained a need to evaluate the optimized configuration from the standpoint of determining suitability of the optimized design vis-à-vis the previously derived optimal configurations. Since modular hypersonic plane is a novel concept therefore there exists no real database with which to compare the design solution for suitability. This signifies the need of evolving an *expert system* that could serve the intended purpose of evaluating the suitability of particular configuration. In recent past expert systems [5] particularly those based on computational intelligence [6] methods as classification tools for aerospace systems have been used for evaluation and model selection of aerospace configurations. Notable in this context are applications that address the issues pertaining to design methodologies such as the evolution of an improved aircraft design cycle that utilizes artificial intelligence (AI) to bring about an overall reduction in the overall design-cycle time [7]. AI has also seen extensive application in the field of spacecraft design. Of particular importance is the recent application of genetic algorithm (GA) [8] based artificial neural network (ANN) [9] as an expert system for controlling the attitude of on-orbit satellite systems [10]. The foregoing researches imply that evolutionary optimization algorithms and machine learning can be hybridized into a single expert system methodology.

Since fully reusable spaceplanes whether in single- or two-stage-to-orbit (SSTO/TSTO) configurations do not exist as yet therefore expert systems for such vehicles are a continuously evolving area of research. In the ensuing research a heuristic-intelligent methodology is proposed, it is based on a hybrid GA-ANN recursive algorithm that uses hybrid GA to obtain vehicle-level optimal solution for mass-modeling of a TSTO vehicle. The optimal solution is treated as a candidate configuration whose efficacy i.e. suitability is classified using ANN algorithm. This classification methodology acts as an expert system to evaluate suitability of the evolved TSTO configuration based on its mass-modeling parameters. This method has the obvious advantages of substantially improving the efficiency of data classification and reducing the complexity of the decision process needed for acceptability of an optimized configuration at conceptual design stage of a spaceplane. The GA-ANN optimization and classification results when evaluated through ve-

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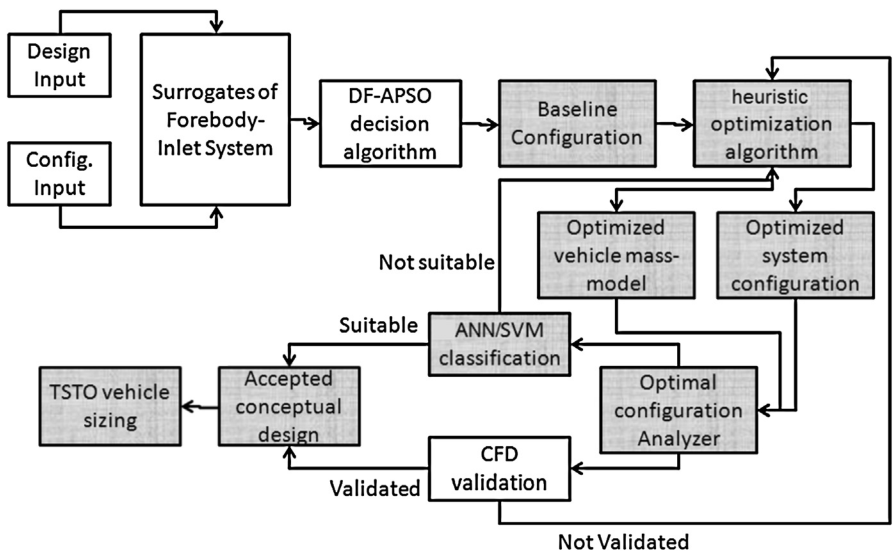

Fig. 1. Vehicle design process of SHWAMIDOF-FI program.

hicle sizing analysis show marked improvement in geometrical parameters of the vehicle. The mass-model database of ANN is validated by classification of two HTSM vehicles [11] and results agree with those obtained from physical findings and support vector machine (SVM) [12] algorithm.

2. The GA-ANN expert system methodology

The GA-ANN optimization and classification methodology is embedded within the design optimization framework of SHWAMIDOF-FI program [13]. This tri-modular program follows the configuration evolution, optimization and analysis process for forebody-inlet component and its TSTO vehicle as depicted in Fig. 1. This process has been evolved on the basis of cognitive-heuristic framework approach [14]. In brief the surrogates of forebody-inlet configurations are evolved using fast and frugal heuristic methods. A cognitive DF-APSO decision algorithm [2] is used to select the baseline configuration which is heuristically optimized using GA/PSO/TIPSO algorithms [3]. The optimized solution yields aerothermodynamic–geometric design for compression component and a mass-model for the TSTO vehicle that constitutes the optimized compression components. Verification and validation of results are accomplished by analyzing the output parameters through either ANN/SVM classification or high-fidelity CFD solutions. If acceptance is accorded to verification and validation parameters then TSTO vehicle sizing is accomplished for lower stage *booster* or else the cycle is repeated from optimization stage. The shaded blocks indicate process components that constitute the TIPSO-SVM methodology.

Classical design methods rely heavily on archival design data, this dependence may be well justified in the wake of large amount of data available for benchmark launch vehicles, however the same is not possible for spaceplanes in either single- or two-stage i.e. SSTO/TSTO configurations. This is because no real hypersonic fully-reusable transatmospheric vehicle exists as yet. Under this scenario any methodology based on archival data may not suffice hence in this paper an inverse design process is proposed as shown in Fig. 2 below. The process mitigates the effect of dependence on historical data and instead uses computational intelligence as its chief source for verification of results. The process depicted in Fig. 2 is fully embedded within the shaded regions of design process shown earlier in Fig. 1 above.

The GA-ANN hybridized method uses mass-model data for TSTO transatmospheric vehicle and optimizes the solution for minimization of initial mass ratio (IMR) and stage masses for each stage of TSTO vehicle. A training data library of previously optimized mass-models is stored and when new data on optimization of vehicle mass-model is generated and passed to artificial neural network (ANN) it is classified for suitability by comparison with the stored training data. If the new data is classified as *suitable* it is stored and processed for vehicle sizing and an accepted conceptual design of vehicle is evolved. In case it fails the classification test then the data is returned back to optimization stage till an optimal solution can be achieved.

2.1. The GA optimization scheme

Genetic algorithms [8,15] were inspired by evolutionary theory [16]. A genetic algorithm starts with several random solutions called the *population*. The strongest members of the population – those with lowest cost – are chosen and modified either through *mutation* (minor changes) or through *crossover* (trait combination). This creates a new population, known as *next generation*, and over successive generations the solution improves. The process stops when a certain threshold has been achieved, when the population has not improved over several generations, or when a maximum number of generations have been reached. The algorithm then returns the best solution that has been found in any generation.

GA is typically used to solve the class of problem called *cost function* whereby the algorithm attempts to select values that minimizes the output of a cost function. A cost function is any function that takes a guess at a solution and returns a value that is higher for worse solution or lower for better solutions. Cost functions used with GA can have a single variable or can be *multivariable* thus making the problem more cumbersome to solve – that is it's not always clear which is the best variable to change for the solution to improve. Although GA is a global optimization solution meaning thereby that it can handle problems involving large search spaces and still returns a solution that is the *global minimum*, nevertheless it is known to have limitations when the dimensionality of the problem is increased. In such cases GA often gets trapped into *local optima* and is then unable to recover from this *search trap*. Such scenarios need to be avoided and for that purpose *GA tuning algorithms* are introduced into the main algorithm that assists in overcoming local optimal trapping. Since the problem case discussed in this paper also deals with a multivari-