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A NEURAL NETWORK APPROACH FOR WEAPON-TARGET ALLOCATION

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A NEURAL NETWORK APPROACH FOR WEAPON-TARGET ALLOCATION

J. Berger
Command and Control Division
Defence Research Establishment Valcartier
P.O. Box 8800
Courcelette, Québec, CANADA G0A 1R0
Email: jeanb@quebec.drev.dnd.ca

ABSTRACT

The decision-making process responsible for weapon-target allocation (WTA) constitutes a key component for battle management command and control systems. Real-time constraints imposed on such systems involve very strict computational requirements on the resolution of this challenging problem. In that respect, the classical formulations considered for modeling WTA, generally prone to suffer from combinatorial explosion, suggest the development of cost-effective optimization-based techniques. In this paper, a neural network-based optimization algorithm is proposed in order to solve static WTA problems. Largely inspired from the principles of Hopfield neural networks, it exploits implicit parallelism for computing fast near-optimal solution while maintaining constraint satisfaction. The approach is currently being investigated in the context of naval anti-air warfare applicable to single and multiple platforms.

I. INTRODUCTION

The impact of weapon-target allocation, a specific task of battle management/command, control, and communications (BM/C3), is of paramount importance in real-time naval command and control systems. This component alone constitutes a key element in the overall air defence system. Survivability of a warship against direct and potential threats depends partly upon the capability of the embedded decision-making process to timely allocate resources.

In this paper, we consider the resolution of the static weapon-target allocation problem using the neural network (NN) technology. From a computational viewpoint this stochastic constrained-optimization problem has proved to be NP-complete [1], meaning that exponential time is required to determine optimal solution. However, the implicit parallelism that emerge naturally from the underlying algorithm makes NNs a very attractive avenue to be explored, giving flexibility to reach a trade-off between execution time and the quality of the computed solution.

The paper is organized as follows. The static WTA problem is first introduced in Section II. The intrinsic complexity of the problem involved is emphasized, and the need for the development of efficient algorithms underlined. Then, Section III describes a neural-network approach to address the static WTA problem. It focuses on Hopfield and stochastic NN-based algorithms to solve combinatorial optimization problems. Then, ongoing investigation is briefly described, and a further perspective to tackle more complex models is discussed. A short summary is finally made in Section IV.

II. PROBLEM MODEL

A. Basic Characteristics

The basic characteristics describing a weapon-target allocation problem include the objective pursued, the availability of dynamic information, the level of uncertainty to be considered into the formulation and the resource constraint requirements. However, it becomes increasingly difficult to define a proper framework as more elements are included into the problem model. A large variety of models and relevant references for WTA may be found in [2].

Given the complexity of the WTA problem, the scope of this paper is limited to a static problem formulation [2]. Consequently, any considerations related to uncertainty, dynamic information and resource constraint requirements are overlooked. The situation is assumed to be perfectly predictable and no resource contention is involved. The objective selected is target-based (weighted subtractive defence) and planning is assumed to take place over a single time horizon (open-loop model).

B. Mathematical Formulation

The problem can be described as follows: n weapon platforms must ensure air-defence against m targets. Each weapon platform i has N_i interceptors and each target is subject to at least r_j and at most R_j shots from the defence. The probability that an interceptor launched from a weapon platform i destroys a target j is determined by the BM/C3 system. Probability p_{ij} depends on the characteristics of the weapon and the target as well as the relative geometry. The static WTA problem of interest consists to minimize the expected leakage value (ELV) of the overall target over a given period of time ΔT:

$$\min_{\{x_{ij}\}} ELV = \sum_{j=1}^{m} V_j \prod_{i=1}^{n} (1 - p_{ij} x_{ij}) \tag{2.1}$$

subject to

$$r_j \le \sum_{i=1}^{n} x_{ij} \le R_j \qquad 1 \le j \le m \tag{2.2}$$

$$\sum_{j=1}^{m} x_{ij} \le N_i \qquad 1 \le i \le n \tag{2.3}$$

$$\sum_{j=1}^{m} \sum_{i=1}^{n} x_{ij} \le \min \{ \sum_{j=1}^{m} R_j ,\ \sum_{i=1}^{n} N_i \} \tag{2.4}$$

$$x_{ij} \in \{0,1\} \quad \forall i,j \tag{2.5}$$

where

n: Number of weapon platforms.

m: Number of targets.

V_j: Value of target j.

p_{ij}: Probability of weapon platform i to destroy target j.

x_{ij}: Decision variable concerning the allocation of weapon platform i to threat j.

r_j: Minimum number of interceptors to be allocated on target j.

R_j: Maximum number of interceptors to be allocated on target j.

N_i: Initial number of interceptors on weapon platform i.

Being computationally intensive, this nonlinear programming problem requires the development of efficient algorithms in order to solve it. In that respect, next section presents a resolution method based on neural networks to deal with static WTA.

III. NEURAL-NETWORK APPROACH

In this section we present how Hopfield (deterministic) and stochastic NN models can be used to address the static WTA problem.

A. Hopfield Neural Network (deterministic):

A Hopfield NN [3] consists of a large number of processing elements interconnected in a way which permits highly parallel computation. Each processing element of the network called "neuron" corresponds to a binary variable in {0,1}. Connections between neurons are characterized by synaptic weights. The resolution of combinatorial-optimization problems using Hopfield NNs consists to determine which neurons should be active (output value: 1) and which should be inactive (output value: 0). The strengths connections or weights are selected in order to minimize a desired objective function commonly known as "energy function".

The neuron input-output relation is defined in terms of a gain function, typically described by a sigmoidal form:

$$x_i = g(u_i) = \frac{1}{2}\left[1 + \tanh(\frac{u_i}{u_0})\right] \tag{3.1}$$

where $u_i \in]-\infty,+\infty[$ represents the internal state of the neuron i $(1 \leq i \leq N)$ and $x_i \in [0,1]$ its output signal. u_0 is a parameter depicting the reference activation level which defines the gain. In the limit of high gain (steep nonlinearity) the output domain corresponds to the binary set $\{0,1\}$.

A neuron i receives the output signals x_j from the other neurons through the input links and is subject to an input bias I_i . As a result , the network input on neuron i is:

$$net_i = \sum_{j=1}^{N} w_{ij} x_j + I_i \tag{3.2}$$

The internal state of a neuron i activated by the network input net_i is dynamically governed by:

$$\frac{du_i}{dt} = -\frac{u_i}{\tau} + net_i \tag{3.3}$$

where τ is the time constant of the neuron. Under certain conditions Hopfield has shown the convergence of the NNs for the following energy function:

$$E(\mathbf{x}) = -\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij} x_i x_j - \sum_{i=1}^{N} I_i x_i + \frac{1}{\tau}\sum_{i=1}^{N}\int g^{-1}(x_i)dx_i \tag{3.4}$$

where

$$\frac{du_i}{dt} = -\frac{\partial E(\mathbf{x})}{\partial x_i} \tag{3.5}$$

Energy monotonically decreases with time until it reaches an equilibrium state corresponding to a local minimum. The evolution of the system to specific local minima highly depends upon initial conditions. It is worth mentioning that in the limit of high gain, the minima of the energy function occur at the corners of a N-dimensional hypercube (i.e. x_j = 0 or 1). This observation makes NNs an attractive approach to investigate discrete systems, even though general functions to be minimized differ from the quadratic form (3.4). The derivation of a well-suited energy function might potentially provide good but not necessarily optimal performance for the problem of interest.

Artificial Neural Network-based Algorithm for WTA:

In order to address the static weapon-target allocation problem (2.1), a deterministic neural network of size m*n is defined where each neuron-like element denoted (i,j) refers to a weapon-target pair. The output signal of a processing element (i,j) corresponds to the "extended continuous" decision variable x_{ij} eventually converging to a binary value within $\{0,1\}$. The solution to this constrained-optimization problem combines the Hopfield NN method and the Lagrange multipliers differential method [4]. The related energy function E is given by:

$$E(\mathbf{x},\lambda) = ELV(\mathbf{x}) + \sum_{\alpha} \lambda_\alpha E_\alpha(\mathbf{x}) \tag{3.6}$$

where ELV is defined in (2.1). The penalty term added to ELV involves non-negative constraint functions E_α weighted by Lagrange multipliers λ_α. The continuously differentiable constraint functions E_α tend to vanish when the related constraints are satisfied (equation (2.2) to (2.5)). This contribution to the energy function is aimed to improve system convergence in exploring feasible solutions. The dynamic of this system [4] is governed by:

$$\frac{du_{ij}}{dt} = -\frac{\partial ELV(\mathbf{x})}{\partial x_{ij}} - \sum_{\alpha} \lambda_\alpha \frac{\partial E_\alpha(\mathbf{x})}{\partial x_{ij}} \tag{3.7}$$

$$\frac{d\lambda_\alpha}{dt} = +E_\alpha(\mathbf{x}) \tag{3.8}$$

Recent implementation of this algorithm has shown promising avenues to address the static weapon assignment problem [5]. As an extension to this work, a more extensive study including comparative performance evaluation for serial and massively parallel architectures still remain to be achieved in order to assess the suitability of the approach for real-time applications.

Although the aforementioned NN-based approach shows interesting perspectives, it nonetheless presents some limitations. The convergence of the algorithm is primarily confined to local minima by virtue of its intrinsic determinism, leading potentially in some cases to unsatisfactory results. Moreover, the results obtained may be highly sensitive to initial conditions. A flexible control strategy permitting the search for an optimal solution (global minimum) is then required. An alternative approach is suggested in the following.

B. Stochastic Neural Networks:

As an extension to the Hopfield NN model just presented a stochastic neural network (SNN) is being considered [6] to perform global optimization. Mainly inspired from statistical physics, it exploits simulated annealing. This probabilistic hill-climbing algorithm facilitates the escape from local minima so that global minimum can be reached. Random perturbations are applied to the "system" to permit transitions to states with higher energy level, allowing the search by gradient descent to resume in a new area of the solution space. The conjunction of Hopfield NNs and simulated annealing is obtained by driving the deterministic system (3.5) with a white noise term:

$$\frac{du_i}{dt} = -\frac{\partial E(\mathbf{x})}{\partial x_i} + 2\sqrt{2Tu_0}\cosh\left(\frac{u_i(t)}{2u_0}\right)v_i(t) \tag{3.9}$$

where the stochastic processes $v_i(t)$ are mutually uncorrelated zero-mean and unit-variance white Gaussian noise, that is:

$$E\,[v_i(t)\cdot v_i(s)] = \delta(t-s) \tag{3.10}$$

T is the temperature parameter describing noise intensity. When the noise is sufficiently large the system can escape local minima and converge in probability to the corresponding minimum energy level. If the temperature tends to zero sufficiently slowly global minimum can be found [6]. The problem consists to determine the appropriate schedule T(t) to ensure convergence.

Another technique may be coordinated with the annealing process to contribute finding optimal solution: sharpening. This technique lies in the sharpening of the output gain curve. It consists to slowly decrease over time the reference activation level u_0. During the early stages when the temperature is high, a nearly flat curve is used. As the temperature decreases the sigmoidal curve is made steeper (smaller u_0). The use of a low-gain system in the early stages permits a longer search period within the hypercube (search space). However, sharper nonlinearity becomes essential at later stages in order to ensure that the corners of the hypercube be reached.

A study is being conducted at DREV to investigate stochastic and Hopfield NN-based optimization algorithms to solve the static WTA problem. It consists to carry out a comparative performance evaluation and assess the suitability of the approach for real-time applications. Typical measures of performance include the quality of the computed solution, and the execution time. Given the implicit parallelism involved into the NN technique, implementations on massively parallel architecture will be considered. Based upon the relative success of the technique, further extensions will attempt to include dynamic characteristics in the model in order to represent scheduling constraints and resource contention issues.

SUMMARY AND CONCLUSION

The weapon-target allocation problem so critical for real-time BM/C3 systems has been considered. The basic characteristics of a related problem model were first introduced and briefly discussed. In order to address the high computational complexity depicted by weapon-target allocation problems, a neural-network-based optimization algorithm was then presented. Largely based upon Hopfield neural networks the proposed approach aims to solve static WTA problems exploiting implicit parallelism in the model. It is believed that the neural network model can reasonably provide acceptable or near-optimal feasible solution. Performance of the approach is currently being investigated in the context of naval anti-air warfare.

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