UDC 004.896

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Artificial intelligence in human oriented design tasks

A new approach for the complete design and development of complex multidisciplinary technical systems is proposed. The framework of computer-aided design interconnected agents for the solution of complex criteria problems is provided.

Universal paradigm for the complete design and development of complex multidisciplinary technical systems.

The use of elements of neural networks and artificial intelligence to help solving complex design tasks have built the foundation for the future research. The main directions are reinforced learning, algorithms fusion such as hybridisation of genetic algorithms of different types or multi-agent modelling and artificial intelligence (AI) [1]. One of the most universal and promising approach is the reinforcement learning [2] build upon the framework of interconnected agents (Fig 1.).

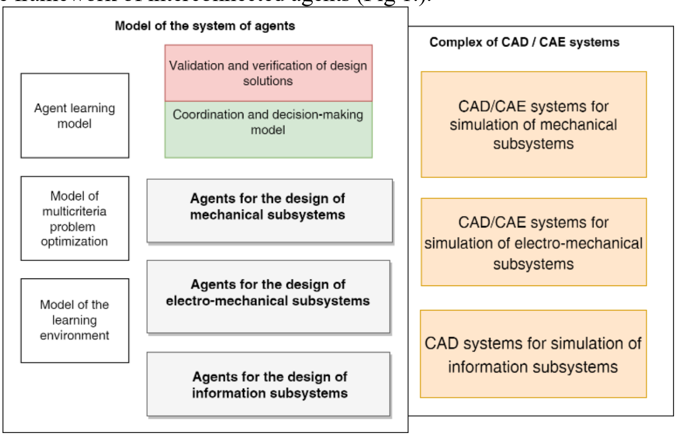

Fig. 1. Multi-agent network for CAD/CAE

This multi-agent approach allows to build arbitrary defined cybernetwork. Dimensions and the scope are limited by the processing capacity of the computers and complexity limits come at the cost of coordination manageability. Thus, it is crucial to build an agent model as complete as possible to be able to integrate it as proactive intelligent agent with the simplest possible communication with the cybernetwork. The problem is as follows:

$$\min_{\theta\in\Phi} J(\theta) = E[Y_0(\theta, \omega)],$$

$$\textit{subject to } E[Y_j(\theta,\omega)] \geq a_j \text{ for } j = 1, \ldots, r-1,$$

where θ is the vector of decision variables, Φ is the constraint set, ω represents a set of pseudorandom numbers, Y_i ($i = 0, ..., r - 1$) is a random response evaluated through simulation, and a_j is the deterministic threshold for constraint j.

Simulation-based optimization can be the best solution for the complex problems when there exist computer-aided modelling and simulation analysis integrated CAD/CAE system. The main solution principle is iterative and coordinated improvement of the solution by simulation [3].

Principle of self-improvement for the solution of complex criteria problems.

The most important trait of the intelligent agent is the ability to build its own self reasoning called policy. Policy in algorithms of the reinforcement learning could be self-improved by different ways. The most advanced algorithms are listed in the Table 1 [4]:

Table 1. Multi-agent deep reinforcement learning algorithms

Challenges	Value-based	Actor-critic	Policy-based
Partial observability	DRQN; DDRQN; RIAL and DIAL; Action-specific DRQN; MT-MARL; PS DQN; RL as a Rehearsal (RLaR)	PS-DDPG and PS-A3C; MADDPG-M	DPIQN and DRPIQN; PS-TRPO; Bayesian action decoder (BAD)
Non stationarity	DRUQN and DLCQN; Multi-agent concurrent DQN; Recurrent DQN-based multi-agent importance sampling and fingerprints; Hysteretic-DQN; Lenient-DQN; WDDQN	MADDPG; PS-A3C	PS-TRPO
Continuous action spaces		Recurrent DPG; DDPG	TRPO; PS-TRPO
Multi-agent training schemes	Multi-agent extension of DQN; RIAL and DIAL; CommNet; DRON; MS-MARL; Linearly fuzzified joint Q-function for MAS	MADDPG; COMA	
Transfer learning in MAS	Policy distillation; Multi-task policy distillation; Multi-agent DQN	Progressive networks	Actor-Mimic

The main problem with all multi-agent deep reinforcement algorithms is that they are designed to overcome specific problems to find the solution for the real-world problem. Firstly, to apply proper algorithm model of the environment must be researched for the observability. Then it must be decided how to train the agents: to train all agents at the same time exposes the non-stationarity problem, sometimes it is more efficient to train agents independently, transfer knowledge between agents or integrate centralized learning. Then for the continuous environments decision must be made whether to use discretization or apply continuous states and actions algorithms.

Computer-aided design is the core and the design subject must be modelled and simulated as close as possible to real systems.

The approach of building an intelligent CAD system ensures the integration of existing CAD/CAE systems into a single autonomous complex, in which a human operator defines the criteria and restrictions within which an AI-assisted multi-agent system is allowed to manage automated operations. Simulation agents with elements of the CAD/CAE system use reinforcement learning algorithms to solve the problem of multi-criteria decision-making, resulting in an improved search space for design solutions in terms of using prior knowledge.

The main benefits of the approach are:

1. Improved accuracy.
2. Can automate tasks that are time-consuming or infeasible for humans. Examples are analyzing complex multicriteria tasks and provide portfolio of solutions.
3. Can be trained to make predictions based on past data. This can be useful for the improvement of the technical task by AI.
4. Can perform tasks and guidelines better than humans.

Conclusions

Application of the deep reinforcement learning for the design and development of complex multidisciplinary technical systems allows to decompose the overall task of design and development into a set of different procedures of a multi-agent system. Modern design process compatible with the requirements of the fourth industrial revolution requires a change in both methods and systematic procedure in the design and development process – human supervisor architectures armed with the powerful fusion of intelligent agent software is the direction for the industry of the future.

Future research for the current work is to be based on framing NASA systems engineering guidelines with AI.

References

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