UDC: 004.932 https://doi.org/10.15407/jai2022.02.092

ARTIFICIAL INTELLIGENCE, MACHINE LEARNING, AND INTELLIGENT DECISION SUPPORT SYSTEMS: ITERATIVE "LEARNING" SQG-BASED PROCEDURES FOR DISTRIBUTED MODELS' LINKAGE

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Annotation. In this paper we discuss the on-going joint work contributing to the IIASA (International Institute for Applied Systems Analysis, Laxenburg, Austria) and National Academy of Science of Ukraine projects on "Modeling and management of dynamic stochastic interdependent systems for food-water-energy-health security nexus" (see [1-2] and references therein).

The project develops methodological and modeling tools aiming to create Intelligent multimodel Decision Support System (IDSS) and Platform (IDSP), which can integrate national Food, Water, Energy, Social models with the models operating at the global scale (e.g., IIASA GLOBIOM and MESSAGE), in some cases 'downscaling' the results of the latter to a national level. Data harmonization procedures rely on new type non-smooth stochastic optimization and stochastic quasigradient (SQG) [3-4] methods for robust of-line and on-line decisions involving large-scale machine learning and Artificial Intelligence (AI) problems in particular, Deep Learning (DL) including deep neural learning or deep artificial neural network (ANN).

Among the methodological aims of the project is the development of "Models' Linkage" algorithms which are in the core of the IDSS as they enable distributed models' linkage and data integration into one system on a platform [5-8]. The linkage algorithms solve the problem of linking distributed models, e.g., sectorial and/or regional, into an inter-sectorial inter-regional integrated models. The linkage problem can be viewed as a general endogenous reinforced learning problem of how software agents (models) take decisions in order to maximize the "cumulative reward". Based on novel ideas of systems' linkage under asymmetric information and other uncertainties, nested strategic-operational and local-global models are being developed and used in combination with, in general, non-Bayesian probabilistic downscaling procedures.

In this paper we illustrate the importance of the iterative "learning" solution algorithms based on stochastic quasigradient (SQG) procedures for robust of-line and on-line decisions involving large-scale Machine Learning, Big Data analysis, Distributed Models Linkage, and robust decision-making problems. Advanced robust statistical analysis and machine learning models of, in general, nonstationary stochastic optimization allow to account for potential distributional shifts, heavy tails, and nonstationarities in data streams that can mislead traditional statistical and machine learning models, in particular, deep neural learning or deep artificial neural network (ANN). Proposed models and methods rely on probabilistic and non-probabilistic (explicitly given or simulated) distributions combining measures of chances, experts' beliefs and similarity measures (for example, compressed form of the kernel estimators). For highly nonconvex models such as the deep ANN network, the SQGs allow to avoid local solutions. In cases of nonstationary data, the SQGs allow for sequential revisions and adaptation of parameters to the changing environment, possibly, based on of-line adaptive simulations. The non-smooth STO approaches and SQG-based iterative solution procedures are illustrated with examples of robust estimation, models' linkage, machine learning, adaptive Monte Carlo optimization for cat risks (floods, earthquakes, etc.) modeling and management.

Keywords: ASI, Intelligent multimodel Decision Support System (IDSS), Platform (IDSP), neural network (ANN).

Linking optimization models under ASI

In the following, we illustrate the application of an iterative SQG-based solution procedure to a problem of distributed models' linkage, i.e., linking the individual models in a decentralized fashion via a central planner (central "hub") without requiring the exact information about models' structure and data (in the conditions of asymmetric information and uncertainty). The sequential SQG solution procedure organizes an iterative computerized negotiation between sectorial (food, water, energy, environmental) systems (models) representing Intelligent Agents (IA). The convergence of the procedure to the socially optimal solution is based on the results of non-differentiable optimization providing a new type of machine learning algorithms.

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negotiation processes between distributed models (agents) have been developed for the design of robust carbon trading markets and for water quotas allocation. The SQG iterative algorithms define a "searching" process, which resembles a sequential adaptive learning and improvement of decisions from data and simulations, i.e., the so-called Adaptive Monte Carlo optimization.

Detailed sectorial and regional models have traditionally been used to anticipate and plan desirable developments of respective sectors and regions. These models operate with a set of feasible decisions and aim to select a solution optimizing specific objective function. Sectors and regions are interconnected through the utilization of common resources. For example, the energy and agricultural sectors often compete for the same land and water resources, which are needed for crops and biofuel production, hydroelectric power generation, and coal mining. To improve the interdependent developments, the sectorial and regional models may be linked together to find an efficient integrated solution.

We consider the problem of linking sectorial and regional LP models under ASI when sectors and regions are not able to share information about their models. This lack of full common information about the LP submodels of the IMs makes LP methods inapplicable for integrated modeling under ASI. Uncertain common full information on goals, feasible decisions, constraints, and corresponding data sets are typical for systems with Big Data and Decision Sets, requiring practically impossible solutions of hard data and decisions harmonization tasks. In the following we introduce an equivalent nonsmooth optimization model and a specific subgradient algorithm generating a sequence of linkages converging to an optimal linkage of LP models under ASI.

Our approach for linking LP models under ASI is based on the parallel solving of equivalent nonsmooth optimization model by a simple iterative subgradient algorithm converging to an optimal linkage. It does not require full common information about models' specification, and this approach can be viewed as a new type machine learning of robust decisions with respect to ASI. In this way, we avoid a "hard linking" of the models in a single code. The approache enables parallel distributed solutions of sectorial and regional models instead of a "harmonized" large scale integrated LP model. This also avoids the practically impossible Big Data harmonization under asymmetric information. Using linked detailed sectorial and regional models also allows for taking into account critically important local details, which are usually hidden within aggregate data.

Sectorial/regional models

As we noted, integrated solution of separate (distributed) sectorial and regional LP models under ASI cannot be accomplished by LP methods. In this section we consider an equivalent nonsmooth optimization model.

Consider K models of sectors and regions utilizing some common resources. The problem of their linkage can be formulated as follows. Let $x^{(k)}$ be a vector of decision variables in sector/region k and assume that each sector/region aims to maximize its net profits

$$\langle c^{(k)}, x^{(k)} \rangle \to max, \quad (1)$$

subject to constraints

$$x^{(k)} \geq 0, \quad (2)$$

$$A^{(k)} x^{(k)} \leq b^{(k)}, \quad (3)$$

$$B^{(k)} x^{(k)} \leq y^{(k)}, \quad (4)$$

where $\langle c^{(k)}, x^{(k)} \rangle = \sum_j c_j^{(k)} x_j^{(k)}$,

$$k = 1,2,\ldots,K.$$

Here, net unit profits $c^{(k)}$, vectors $b^{(k)}$and matrices $A^{(k)}$ and $B^{(k)}$ define the marginal contribution of solutions into the total demand, resource use, and environmental impact. Thus, we distinguish between the constraints (3) that are specific to sector/region k and the constraints (4) that are part of a common inter-sectorial/inter-regional constraint with sectorial/regional quotas of resources $y^{(k)}$.

Linking the submodels is carried out by "linking" vectors $y^{(k)}$. There is a nonempty set of linking vectors $y^{(k)}$ characterizing the feasible conditions of linkage described by linear constraints

$$\sum_{k=1}^{K} D^{(k)} y^{(k)} \leq d. \quad (5)$$

Here matrix $D^{(k)}$ defines the marginal sectorial/regional resources use with a vector of resources d, $d \geq 0$. The problem of models' linkage under full information can be formulated as a total net profit maximization

$$\sum_{k=1}^{K} \langle c^{(k)}, x^{(k)} \rangle \to \max \quad (6)$$

s. t. to constraints (2)-(5), $k = 1,2,\ldots,K$.

By asymmetric information (ASI) of sectors/regions we mean that a sector/region k does not know $b^{(k)}$, $c^{(l)}$, $A^{(l)}$, $B^{(l)}$, $x^{(l)}$ of other sectors/regions, $l \neq k$. Therefore, the integrated LP model (2)-(6) under ASI cannot be solved by LP method due to the lack of common information about submodels.

Nonsmooth model

Let us formulate a basic nonsmooth optimization model that is equivalent to the integrated LP model under ASI. This basic model can be solved by a specific iterative subgradient linkage algorithm.

For a given vector $y = (y^{(1)}, \dots, y^{(K)})$ let us denote by $F(y)$ the optimal value of function (6) under constraints (2)-(4). Therefore,

$$F(y) = \sum_{k=1}^{K} f^{(k)}(y),$$

where $f^{(k)}(y) = (c^{(k)}, x^{(k)}(y))$ are concave nonsmooth functions. In this function $x^{(k)}(y)$ are optimal solutions of (1)-(4).

The required linkage algorithm is defined as a subgradient procedure maximizing function $F(y)$ s.t. the joint constraints (5). These constraints define the feasible set of the algorithm, which can be denoted also as Y. Therefore, an optimal solutions maximizing $F(y)$, $y \in Y$, defines also an optimal linkage or a solution of the integrated LP model under ASI. In the following we assume the existence of solutions $x^{(k)}(y)$, $y \in Y$, for all k.

Iterative linking under ASI

Iterative linking

Let us consider a sequence of approximate solution $y^s = (y^{s(1)}, \dots, y^{s(K)})$ for iteration $s = 1,2,\ldots$ of the algorithm. For given quotas y^s independently and in parallel, sectors/regions solve models (1)-(4), $k = 1,2,\ldots,K$, and obtain primal solutions $x^{s(k)} = x^{s(k)}(y^s)$ together with the corresponding solutions $(u^{s(k)}, v^{s(k)})$ of the dual problems

$$\langle b^{(k)}, u^{(k)} \rangle + \langle y^{(k)}, v^{(k)} \rangle \to \min, \quad (7)$$

$$A^{(k)} u^{(k)} + B^{(k)} v^{(k)} \geq c^{(k)}, \quad (8)$$

$$u^{(k)} \geq 0, v^{(k)} \geq 0,\ k = 1,2,\ldots,K. \quad (9)$$

The next approximation $y^{s+1} = \left(y^{s+1(1)}, \ldots, y^{s+1(K)}\right)$ is derived by a social planner (hub) as

$$y^{s+1} = \pi_Y(y^s + \rho_s v^s),\quad s = 1,2,\ldots, \quad (10)$$

where ρ_s is an iteration-dependent step-size multiplier and $\pi_Y(\cdot)$ is the orthogonal projection operator onto set Y.

Vector v^s is a generalized gradient or a subgradient of function $F(y)$ at $y = y^s$. The step-size ρ_s is chosen from rather general and natural requirements: $\rho_s \geq 0$, $\rho_s \to 0$, $\sum_{s=1}^{\infty} \rho_s = \infty$, (e.g. $\rho_s = 1/s$), because subgradients (generalized gradients) are not, in general, the increasing directions of functions. The proposed linkage algorithm for problems under ASI (10) requires additional condition $\sum_{s=1}^{\infty} \rho_s^2 < \infty$ to enable the convergence of not only function $F(y^s)$ but also of the solutions y^s (see Annex). This allows us to propose a simple stopping criterion (see Step 4, Algorithm) enabling parallel optimization of interdependent sectors by (10).

Algorithm

Let us assume, there is a network of distributed computers connecting submodels, say sectors, with a central hub computer. The linkage algorithm can be summarized as follows:

Step 0: Initialization. Sector k, $k = 1,\dots,K$, chooses initial vectors $y^{0(k)}$ of resource quotas and submits it to the central computer (hub). The computer projects $y^0 = (y^{0(1)}, \dots, y^{0(K)})$ onto the set Y defining a first feasible approximation $y^1 = (y^{1(1)}, \dots, y^{1(K)})$; set $s = 1$

Step 1: Generic step. Suppose by the beginning of iteration s the algorithm arrived at vector $y^s = (y^{s(1)}, \dots, y^{s(K)})$. Then on iteration s the algorithm proceeds as follows.

Step 2: All sectors k receive $y^{s(k)}$ and solve models (1)-(4) independently. Shadow prices $v^{s(k)}$ of common resources (constraints (4)) are submitted to the central computer (hub).

Step 3: The central computer calculates $y^s + \rho_s v^s$ with a step-size $\rho_s = c_s/s$, where c_s is a scaling parameter, $\underline{c} \le c_s \le \overline{c}$ for some constants $\underline{c}, \overline{c}$. It regulates ρ_s so that the product $\rho_s v^s$ corresponds to the scale of y^s. Vector $y^s + \rho_s v^s$ is projected onto the set Y and defines y^{s+1}. Sectorial/regional computers receive corresponding components of y^{s+1}.

Step 4: All sectors independently check stopping criteria. Sector k calculates non-negative difference $\varepsilon_k(s) = (b^{(k)}, u^{s(k)}(y^s)) + (y^{s(k)}, v^{s(k)}(y^s)) - w_k(c^{(k)}, x^{s(k)}(y^s))$ and submits values $\varepsilon_k(s)$ to the central computer of the hub.

If $\sum_k \varepsilon_k(s) \le \varepsilon \ge 0$, where ε is an admissible accuracy, then the algorithm stops. Otherwise, it continues with an iteration increment of 1 and returns to step 1.

The convergence theorem shows that the parallel independent optimization and linkage of sectors/regions according to this algorithm without revealing sectorial/reginal information is possible due to the requirement $\sum_s \rho_s^2 < \infty$. This allows to prove the convergence of solutions (linkages) y^s rather than the convergence of objective function $F(y^s)$.

The convergence of the proposed linkage algorithm under ASI is based on the theory of (continuously) non-differentiable optimization.

Conclusions

Traditional integrated modeling (IM) is based on developing and aggregating all relevant (sub)models and data into a single integrated linear programming (LP) model. Unfortunately, this approach is not applicable for IM under asymmetric information (ASI), i.e., *when "private" information about sectoral/regional models is not available or it cannot be shared by modeling teams (sectoral agencies).* The lack of common information about LP submodels makes LP methods inapplicable for integrated LP modeling.

We discussed a new approach to link and optimize distributed sectoral/regional optimization models providing a means of decentralized cross-sectoral coordination in the situation of ASI. Thus, the linkage methodology enables to investigate policies in interdependent systems in a "decentralized" fashion. For the linkage, the sectoral/regional models don't need re-coding or reprogramming. They also don't require additional data harmonization tasks. Instead, they solve their LP submodels independently and in parallel by a specific iterative subgradient algorithm for nonsmooth optimization. The submodels continue to be the same separate LP models. A social planner (regulatory agency) only needs to adjust the joint resource constraints to simple subgradient changes calculated by the algorithm.

The proposed computational algorithm is based on subgradient methods invented for the optimization of non-smooth systems, which may be subject to shocks and discontinuities. Therefore, these methods will be naturally developed further for linking stochastic sectorial models with known marginal distributions of sectorial uncertainties, into cross-sectorial integrated models with joint distributions of collective systemic risks induced by sectorial uncertainties and decisions maximizing a stochastic version of the function (6). It is worth noting that the algorithm can also carry out the linkage of dynamic systems using the same equations. Fundamentally important possible extension of the presented method is the case of stochastic sectorial/regional models with interdependent uncertainties, which can be shaped by linking decisions of various agents. The mitigation of floods by new land use decisions, for example, affect flood scenarios. As a rule, this makes it impossible to separate scenario generations and optimization processes calling for linking both simulation and optimization procedures in a similar manner to algorithm (10), thus combining simulations of scenarios, new optimization steps, new simulation of scenarios, and so on. In this case we can think of new type machine learning processes.

While in this paper, we meant linking regional and/or sectorial models when referring to model linkage, more generally, linking models may refer to different local-global scales. Therefore, the linkage problem can also be formulated much more generally in terms of sub-models and integrated models and the approach presented in this paper can still be applicable.

The linkage of models is, in a sense, opposite to decomposition methods. While in the decomposition we split an existing integrated optimization model into a number of smaller sub-models, in the linkage we obtain an integrated model of the system by linking existing explicitly unknown sub-models. The proposed procedure provides a flexibility enabling the simultaneous use of linkage and decomposition procedures, in other words, endogenously disaggregating models to make their further integration (linkage) more efficient.

Acknowledgements

The development of the presented methodologies and models was supported by a joint project between the International Institute for Applied Systems Analysis (IIASA) and National Academy of Sciences of Ukraine (NASU) on “Integrated robust modeling and management of food-energy-water-land use nexus for sustainable development”. The work has received partial support from the Ukrainian National Fund for Strategic Research, grant No. 2020.02/0121, and project CPEA-LT-2016/10003 jointly with Norwegian University for Science and technology. The paper contributes to EU PARATUS (CL3-2021-DRS-01-03, SEP-210784020) project on “Promoting disaster preparedness and resilience by co-developing stakeholder support tools for managing systemic risk of compounding disasters”.

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The article has been sent to the editors 14.11.22
After processing 10.12.22