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Data-Driven Modeling in Plant Tissue Culture

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ABSTRACT

During *in vitro* propagation, *de novo* organs such as buds, shoots, and roots can be achieved under chemical and physical conditions from explant. Some physical conditions such as types, age, size, density, position, and source of the explants, light intensity, and temperature and also some chemical conditions including macro and micro nutrients, amino acids, vitamins and other nitrogen elements, organic supplements, carbon sources, agar, and plant growth regulators have a positive influence on different stages of plant tissue culture. Therefore, data-driven modeling can be applied for better understanding the effect of the mentioned physical and chemical conditions *in vitro* culture. Data-driven modeling is known as an effective alternative for optimization of biological processes and non-linear multivariate modeling. The present study aimed to describe some useful data driven models such as Artificial neural network (ANN), Generalized least squares regression (GLSR), Random Forests (RF), Self-organizing maps (SOM), Reactor modeling, Genetic programming, and Tree encoding and ultimately, the use of these data-driven models was explained in different stages of plant tissue culture. In conclusion, all of these data-driven models can be employed for predicting and optimizing the physical and chemical conditions for introducing an accurate, useful, and applicable regeneration protocol.
KEYWORDS: Generalized Least Squares Regression; Artificial Neural Network; Random Forests; Reactor Modeling; Genetic Programming; Tree Encoding; *in vitro*.

1. INTRODUCTION

Plant tissue culture including some technics that applied for vegetatively propagated the plant by culturing a tiny part of living tissues (explant) under the sterile condition on artificial growth medium [5, 15]. The shoots and roots were regenerated from explant, and finally, the whole plant was growth under certain culture. Micropropagation is a method that produces the whole plant via plant tissue culture from tiny parts of explant such as shoots, nodes, meristems, embryos, and roots. Also, micropropagation is broadly used for commercial purposes [5, 14].

Regarding data-driven modeling, data are analyzed in the system for investigating the relation with the system state variables without considering the physical behavior of the system [6]. In another word, this type of modeling is in direct contrast with physically based modeling. Thus, this review explains the mechanical behavior of the system [6, 18, 23]. Data-driven modeling has a close connection with the various areas such as data mining, machine learning, and statistics [21]. On the other hand, data-driven modeling does not depend on the large-scale database as well as the analysis of secondary data. Also, data-driven modeling is an applicable model when it can apply based on the use of inexpensive and basic measurement signals for producing parsimonious models that have a good performance [6, 8, 21]. The given discrimination is confusing, and often, the same methods can be used for data-driven modeling [25].

Data-driven modeling is known as an effective alternative for optimization of biological processes and non-linear multivariate modeling [21]. Neural network method is responsible as an alternative method for the polynomial regression method, for estimating various complex mathematical functions to interpret many unpredictable datasets [4, 29, 39]. Data-driven modeling has been found to be accurately usable for different experiments with various numbers of data points, which makes it possible to apply more experimental designs in rather to may statistical approaches [21]. According to recent studies, the effectiveness of data-driven modeling for using in plant tissue culture for different aims such as predicting shoot number and average shoot length [4], or the root numbers and root weight per plant [27, 39] has been demonstrated. The aim of this review is to describe the techniques of Data-Driven modeling as an instrument for analyzing data and their usage in plant tissue culture for clustering, estimation, prediction, classification, and simulation.

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2. DATA-DRIVEN MODELING (DDM)

DDM is known as an efficient alternative model in the situation that mechanistic models are not applicable. In DDM, data prepare a system of analyzing in order to find out relatives among the system state variables with using any explicit knowledge of the system's physical behavior. The techniques that employed in DDM have been developed from various spheres such as machine learning and computational intelligence [16, 25]. In spite the fact that DDM seems to be a cheap and limited methods, its easy utilization is an exceptional advantage especially based on basic, inexpensive on-line measurement signals [21]. Data-driven models are also easy to use when the rate of data is much higher for analyzing by different methods [21, 25], which often occurs in plant tissue culture [4]. The major problem of DDM is its inability to treat with changing environment such as changing in process control because they are not considered in this model [25]. DDM will not be useful in a situation that there is no connection between the other variables and response variable or the data quality is poor. For these reasons that mentioned above, generated data-driven models requires expert knowledge and must be used carefully [6]. However, the investigation could be simplified if transparent models are used and if the modeling is led by the principle of parsimony, which accurately suggests choosing the possible description of a phenomenon (that is an example of preferring simple over complex models). Therefore, it is more delicate to choose the applicable and efficient modeling tool for software-sensor generation [21]. In *in vitro* propagation methods, the potent non-linear modeling techniques might be more applicable due to the dynamic nature of the plant tissue culture processes [29]. Also, parsimonious linear models might be preferred by considering the requirement of models, especially those that depend on little expert knowledge. The suitable modeling techniques may predict not only a software-sensor value but also indicated some estimates of probability to it [39].

2.1. GENERALIZED LEAST SQUARES REGRESSION (GLSR)

The GLSR is known as a type of linear modeling tool. In contrary with the OLS (ordinary least squares) estimation tool, Generalized least squares estimation was not completely depend on the hypothesis that the residuals have not correlated with each other and also they have constant variance [12]. This is a critical characteristic because auto-correlated residuals commonly occur in the case of treating with incomplete models and time series data [9]. Backward-elimination is employed in order to achieve the suitable subset of regression variables by considering the Bayesian information criterion (BIC), which considers not only the quality of the fit but also correct complex models [2].

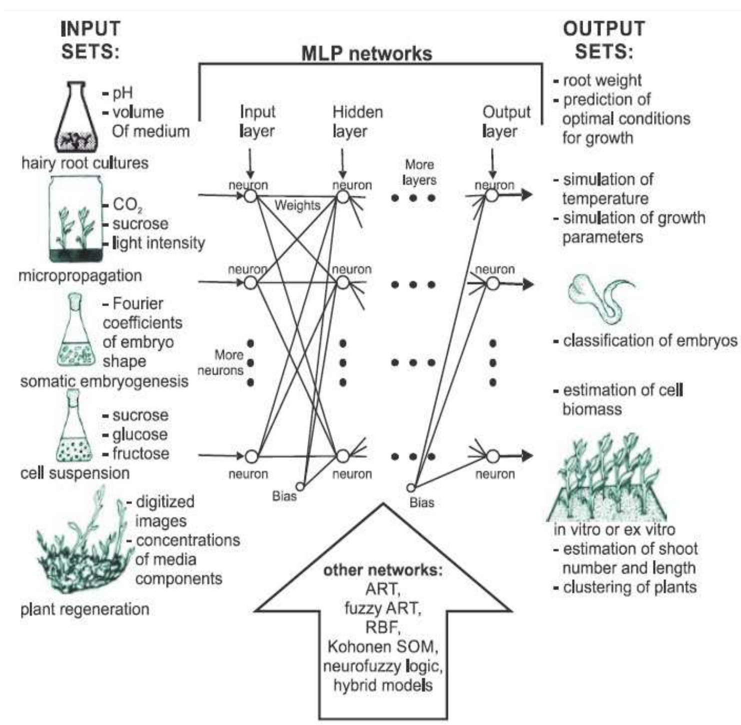

Figure 1. The structure of actual artificial neural network application in plant in vitro culture [39].

2.2. ARTIFICIAL NEURAL NETWORK (ANN)

The ANN is known as a common supervised non-linear statistical data modeling method [4]. According to this review, a multilayer perceptron along with single hidden layer is assumed, which a feed-forward ANN is. All neurons are based on a sigmoidal activation function, except for the neurons in the output layer that possess a linear activation function. The network is applied to a back-propagation learning [39], and early-stopping is employed to inhibit over fitting. The practice-optimal number of hidden units is a dependent problem and estimated for each data set by using several networks with a vast number of hidden neurons (Fig. 1).

2.3. SELF-ORGANIZING MAPS (SOM)

The SOM are based on a noise-tolerant variant of ANNs that utilized by unsupervised learning, basically introduced by Kohonen [19]. They learn to predict input data in a non-linear fashion from a high-dimensional data-space onto a lower-dimensional discrete lattice of neurons on an output layer, named feature map [13, 24]. This is done in a topology-conserving way, which described in this way that neurons had similar input patterns when they located physically close to each other [19].

Each neuron has assumed a prototype vector has the similar dimensionality as the input data [13]. The quantification error (q.e), indicates how well an input vector is present in the SOM and can be pondered as a means for software-sensor self-diagnosis [19]. For instance, the more uncertain the prediction, the higher the q.e. The models that described in this paper have a two dimensional-hexagonal feature map [26].

The number of neurons and the ratio of the side lengths are investigated taking into account the size of the data set [26]. The measure of topological relevance (MTR) is responsible for ranking the necessity of the variables [19, 26].

2.4. RANDOM FORESTS (RF)

The RF is another common machine-learning technique [33]. Random forests are a non-linear ensemble classifiers that build based on aggregation of a large selection of regression or classification trees [38]. The RF technique has an exceptional merit that it conducts notably well with very little tuning required [38] and is not prone to over-fitting [33]. Therefore, it has a suitable performance for highly automated data-driven modeling methods. The averaged response of all trees was obtained when RF is employed for regression. The importance of the regressor variables can be estimated with some samples that not selected in the bootstrap sub-samples for constructing a tree [36].

2.5. REACTOR MODELING

Two types of the reactor (CSTR and PFR) were employed to model hydraulic characteristics. By connecting these basic reactors serially or parallel, even complex circumstances can be modeled [35]. Each reactor has one or more outflows and also a reactor with more than one outflow can be assumed as a reactor with a subsequent flow divider [20].

2.6. GENETIC PROGRAMMING (GP)

GP is one of the search algorithm tools that inspired by nature [37]. It seems to evolve mathematical expressions or computer programs by imitating biological evolution. The new generations are bred by Starting with a population of individuals based on random programs. The fitness of each person is calculated during each generation by a fitness function [22]. The fittest one has a high chance to survive in the next generation. They can be duplicate unaltered (reproduction), promote random changes (mutation), or used to produce new offspring by the interaction of two parents (crossover) [7]. When a given fitness criterion is a maximum number of generations is reached, the GP process will complete. This process is repeated until a given fitness criterion is met or a maximum number of generations is reached [7].

The developed, tree-like computer programs can be different in length that is known as an important feature of GP. Other merits like the absence of a tendency for the entire population to converge does not necessary need to be known in advance [7]. A terminal set and a function set in GP can select to construct the programs. Also, to calculate the fitness of data, they need to be specified. A grammar-based paradigm is selected in this paper with a context-free grammar that includes a set of reproduction rules, function nodes, and terminal nodes that determine for each function the possible child function(s) and a beginning symbol (the tree's root). The definition of a grammar avoids the meaningless of generation programs and consequently significantly decreases the search space [37].

Table 1: The function and terminal sets for encoding the reactor models.

Name	Description	Num. children (type)
Function set		
ROOT	Root node (starting node)	2 (Function)
ADF_L	Automatically defined function encoding the model layout	1 (Function)
ADF_R	Automatically defined function encoding the reaction	1 (Function)
PAR	Parallel arrangement	2 (Function)
SER	Serial arrangement	2 (Function)
INV	Invert fluxes of child nodes	1 (Function)
CSTR	Continuous stirred-tank reactor	4 (Terminal)
PFR	Ideal plug flow reactor	3 (Terminal)
VLR	Volume-less reactor, used to encode shortcut flows	1 (Terminal)
R_ZERO	Zero-order reaction kinetics	1 (Terminal)
R_FIRST	First-order reaction kinetics	1 (Terminal)
R_MONOD	Mixed-order reaction kinetics (Monod)	2 (Terminal)
Terminal set		
REACTION	Either NO_R (no reaction) or ADF_R (reaction defined in ADF_R branch)	
ERC_vol	Reactor volume (set of constants)	
ERC_flow	Weight factor for flow distribution (set of constants)	
ERC_k0	Zero-order reaction constant (set of constants)	
ERC_k1	First-order reaction constant (set of constants)	
ERC_q	Maximum activity, Monod kinetics (set of constants)	
ERC_KS	Half-saturation coefficient, Monod kinetics (set of constants)	

2.7. TREE ENCODING

A tree encoding was determined for representing hydraulic reactor models as computer programs. The Table 1 showed the functions and terminals available for this program and the grammar rules are showed in Table 2. All program starts with a ROOT function, which has two child nodes, which splits the program into two branches [1].

Table 2: Grammar rules to prove meaningfulness of the evolved computer programs.

Function	Sets of children available for each descendant of the function
ROOT	{ADF_L}, {ADF_R}
ADF_L	{PAR, SER, CSTR, PFR, VLR}
ADF_R	{R_ZERO, R_FIRST, R_MONOD}
PAR	{PAR, SER, INV, CSTR, PFR, VLR}, {PAR, SER, INV, CSTR, PFR, VLR}
SER	{PAR, SER, CSTR, PFR, VLR}, {PAR, SER, CSTR, PFR, VLR}
INV	{PAR, SER, CSTR, PFR, VLR}
CSTR	{ERC_vol}, {ERC_flow}, {ERC_flow}, {REACTION}
PFR	{ERC_vol}, {ERC_flow}, {ERC_flow}
VLR	{ERC_flow}
R_ZERO	{ERC_k0}
R_FIRST	{ERC_k1}
R_MONOD	{ERC_mu}, {ERC_KS}

The layout of the model (the reactors and their connections) is encoded by the left branch (starting from the ADF L-function) whereas the reaction rate is encoded by the right branch, which can be referenced by reactors of the model. The program tree is recursively decoded starting from the outermost terminals. The inflow and outflow nodes are added once the decoding obtains the ROOT function, resulting in an object-oriented presentation of the hydraulic model [1]. The decoding is indicated in Fig. 2.

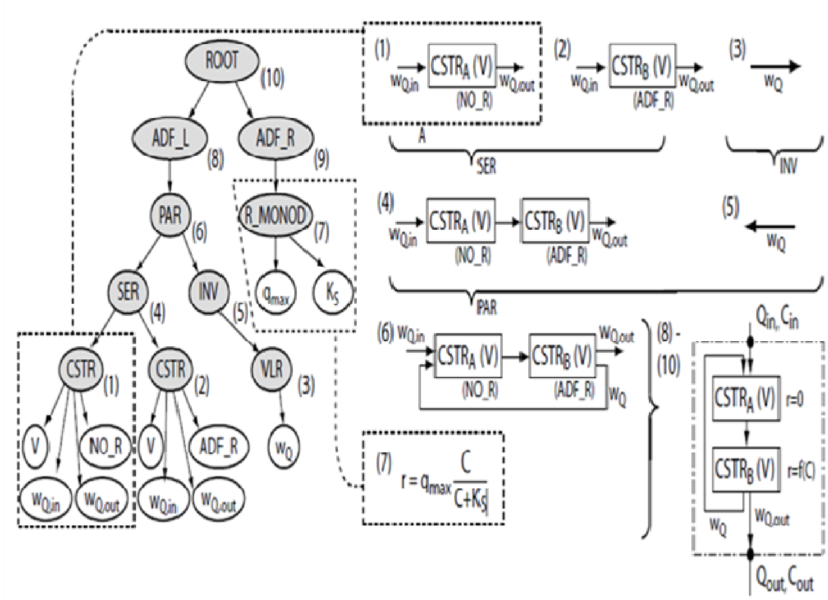

Figure 2: An illustration of the decoding of a GP program. The tree (left) is traversed from the outermost nodes in the ten steps, and the reactor model is extended successively. The extension is graphically illustrated (right), and the resulting model illustrates (bottom right). The volumes V are taken from the ERC_vol set, the weight factors w_Q from the ERC_FLOW set and the reaction coefficients q_{max} and K_S from the ERC_q and ERC_KS sets, respectively [8].

2.8. DATA_DRIVEN MODELING SOFTWARE

For creating DDM, many useful software packages such as Matlab, Statistica Neural Networks, IN Form and Form Rules, SPSS, and Bio-Comp iModel can be utilized. In conclusion, this software is employed in DDM.

3. FACTORS AFFECTING EXPLANT'S REGENERATION CAPACITY

3.1. PLANT MATERIAL

Plant material has a massive impact on the rate of success in tissue culture studies. Some factors that play an important role in explant's tissue culture response 1. Physiological phase of the mother plant, 2. Explant source, age, size, density, and explant position in donor plant, and 3. Genotype. Plant segments employed in *in vitro* culture as explant are root, stem, flower, leaf, ovule, hypocotyl and cotyledon [5, 14, 34].

3.2. CULTURE MEDIUM

The composition of the culture medium is a high paramount factor that affects morphogenesis and growth of plant tissues. The culture medium containing micro and macro nutrients, amino acids or other nitrogen supplements, vitamins, carbon sources, agar, growth regulators, and organic supplements [4]. A vast number of plants that regenerated by *in vitro* culture are discarded as a result of hyperhydricity and chlorosis during *in vitro* propagation of some species of *Prunus* sp. such as GF677 hybrid rootstock [4, 29]. Those physiological disorders may occur based on their origin in the composition of the mineral media, plant growth regulators, the carbon source, and culture conditions [4, 29, 39]. The composition of the mineral media plays a vital role in growth and development, and sometimes they caused a negative influence and physiological problems like those mentioned above in the situation when excessive concentrations are used [28, 39]. The impact of a vast number of variables applied in the development of media (concentrations and type of minerals) on the growth parameters to be fully understood by using conventional statistical methods. Recently, thanks to computer technologies, especially artificial intelligence [29], which provided an atmosphere for the researchers to model and better understanding the role of the elements contributed on plant growth under *in vitro* condition [2]. Data-driven modeling help researchers to understand the cause-effect relationships such as between mineral media culture composition and growth (Table 3). A deep understanding of the elements affecting the result of a process allows its improvement, lastly, and its optimization [39].

3.3. CULTURE CONDITIONS

After explants inoculated on culture medium for various goals, they must be kept in growth chambers with controlled environmental elements such as temperature and light [14]. Also, various plants may need various environmental elements for successful culture. By fluorescent tubes, we can detect lighting in culture rooms [4]. Control equipment of tubes should be adjusted outside the growth chamber. Additionally, extra cooling is necessary in the case of increasing the heat inside the room so there should be a cooling system to keep constant temperature conditions Fluorescent tubes can be utilized under the shelves, above the cultures which prepare a more uniform irradiation for the cultures. In spite the fact that 16 h light and 8 h dark is commonly used, there may be some differences for various plants [5].

For successful tissue culture, it is necessary to control the temperature in culture [29]. The temperature variation in growth chamber should be ±1ºC. Also, changing in temperature regime can promote stress in cultures which are the major reason for being unsuccessful in plant tissue culture. Therefore, it highly recommends working with many growth chambers instead of working only with one [5]. Each of the factors that mentioned above can be used as an input for Data-Driven Model and some parameters such as total biomass, the number and the length of shoots and roots and etc., can be measured as an output. According to the table 3, there are some studies that conducted based on the mentioned Data-Driven Models.

Table 3: Studies in which Data-Driven Modeling (DDM) employed in the plant tissue culture.

Species	Step of tissue culture	Applied model	Reference
Glycyrrhiza	hairy root cultures	Artificial Neural Network and Regression Network	Prakash et al. [31]
***Vitis vinifera* L.**	rooting and acclimatization	Artificial Intelligence	Gago et al. [10]
***Rubus idaeus* L.**	improving growth	Polynomial Regression	Poothong and Reed [30]
Rauwolfia serpentina	hairy root cultures	Artificial Neural Network	Mehrotra et al. [28]
Centella asiatica	multiple shoot cultures	Artificial Neural Network	Prasad et al. [32]
Glycyrrhiza	optimum productivity	Artificial Neural Network	Mehrotra et al. [27]
Prunus	Design of tissue culture media	Artificial Intelligence	Nezami-Alanagh et al. [3]
Pistacia vera	Design of tissue culture media	Artificial Neural Network	Nezami-Alanagh et al. [29]
Pyrus	Design of tissue culture media	Genetic Algorithm and Neural Network	Jamshidi et al. [17]
Prunus	Design of tissue culture media	Genetic Algorithm and Neural Network	Arab et al. [4]
Actinidia chinensis	acclimatization	Artificial Intelligence	Gago et al. [11]

4. CONCLUSIONS

Nowadays, Data-Driven Modeling is the most applicable method and play an important role as a predictive tool for modeling complex biological studies. Based on mentioned studies, neural or neurofuzzy models are known as a most capable method for predicting what will happen under other conditions. Neural modeling can be employed with a limited experiment, that is consequently decreased the costs of *in vitro* culture. In the future, Data-Driven Modeling could be applied for the automation and mechanization of plant breeding programs through plant tissue cultures in terms of quality.

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