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Using LEL and scenarios to derive mathematical programming models. Application in a fresh tomato packing problem

Alejandra Garrido^{a,b}, Leandro Antonelli^a, Jonathan Martin^a, M.M.E. Alemany^c, *Josefa Mula^c

^a LIFIA, Fac. de Informática, Univ. Nac. de La Plata, La Plata, Argentina, <u>garrido@lifia.info.unlp.edu.ar</u>, lanto@lifia.info.unlp.edu.ar, jonathan.martin@lifia.info.unlp.edu.ar,

^b CONICET, Argentina

^c Research Centre on Production Management and Engineering (CIGIP), Universitat Politècnica de València, Valencia, Spain, mareva@cigip.upv.es,*Corresponding author: fmula@cigip.upv.es

Abstract

12 Mathematical programming models are invaluable tools at decision making, assisting managers to uncover otherwise 13 unattainable means to optimize their processes. However, the value they provide is only as good as their capacity to 14 capture the process domain. This information can only be obtained from stakeholders, i.e., clients or users, who can 15 hardly communicate the requirements clearly and completely. Besides, existing conceptual models of mathematical 16 programming models are not standardized, nor is the process of deriving the mathematical programming model from 17 the concept model, which remains ad hoc. In this paper, we propose an agile methodology to construct mathematical 18 programming models based on two techniques from requirements engineering that have been proven effective at 19 requirements elicitation: the language extended lexicon (LEL) and scenarios. Using the pair of LEL + scenarios allows 20 to create a conceptual model that is clear and complete enough to derive a mathematical programming model that 21 22 23 24 25 26 27 28 29 30 effectively captures the business domain. We also define an ontology to describe the pair LEL + scenarios, which has been implemented with a semantic mediawiki and allows the collaborative construction of the conceptual model and the semi-automatic derivation of mathematical programming model elements. The process is applied and validated in a known fresh tomato packing optimization problem. This proposal can be of high relevance for the development and implementation of mathematical programming models for optimizing agriculture and supply chain management related processes in order to fill the current gap between mathematical programming models in the theory and the practice.

Keywords: Language extended lexicon (LEL); scenarios; software engineering; mathematical programming; fresh tomato packing. 31

32 **1. Introduction**

33 There is an increasing interest in mathematical programming models for optimal decision support 34 applications (Dominguez-Ballesteros et al., 2002). Indeed, the development of optimization and 35 decision support tools is needed to obtain all the benefits of transactional information technology 36 (IT), improving the economic performance and customer satisfaction of supply chains 37 (Grossmann, 2005). Along these lines, mathematical programming models have been 38 demonstrated to be powerful optimization tools to support decision makers in many supply chain 39 processes such as: production planning (Alemany et al., 2013), order promising (Alemany et al., 40 2018; Grillo et al., 2017), shortage planning (Esteso et al., 2018), supply chain production and 41 transport planning (Mula et al., 2010), among others. The agriculture sector also faces many 42 complex problems for optimization (Saranya & Amudha, 2017) as it has been reported in some 43 recent works (Cid-Garcia & Ibarra-Rojas, 2019; Grillo et al., 2017; Liu et al., 2019). Some 44 revisions about mathematical programming models applied to different problems in agriculture 45 can be found for supply chain design (Esteso, Alemany, & Ortiz, 2018), fresh fuit supply chain 46 management (Soto-Silva et al., 2016), agribusiness supply chain risk management (Behzadi et al., 47 2018) and crop planning (Jain et al., 2018), among others.

48 Once formulated, mathematical programming models are often implemented as part of a decision 49 support system (DSS), which is thus called model-driven DSS. We refer readers to the work of 50 Udias et al. (2018) regarding an example of recent agricultural model-based DSS. These types of 51 DSSs allow the user to make what-if analysis and define different scenarios without the need to 52 understand the complexities of mathematical programming models (Mundi et al., 2013). Mir et al. 53 (2015) provide an extensive revision of DSS application in agriculture noting their main 54 weaknesses, most of them related to the poor involvement of stakeholders in the DSS construction 55 process, which our methodology aims to overcome: failure to support stakeholder participation 56 before and after development stages, failure to support the relationship between stakeholders and 57 experts/developers, low adaptation, complexity with user inputs and under-definition of end users. 58 Moreover, the construction of mathematical programming models is a complex and very time-59 consuming process, which requires an expert to acquire a deep understanding of the modelling 60 domain, context of use, decision making activity, and to learn the complete set of constraints from 61 the problem under study. All this problem knowledge should be acquired before the model is 62 constructed, because any change that occurs afterwards might imply a whole redesign and 63 implementation of the model. For this reason, mathematical programming model construction 64 should be preceded by a conceptual modelling activity whose natural use in the field of applied 65 mathematics has been pointed out by Lesh (1981) and Lesh et al. (1983).

During conceptual modelling, different tools are used, like Bizagi, BPWin, iGrafx, Process
Modeler, System Architect and Visio, to help understand the domain, the flow of data, products,
decisions and the interaction among parties, and to elicit requirements as completely as necessary
(Armengol et al., 2015; Giannoccaro & Pontrandolfo, 2001; Hernández et al., 2008; Mula et al.,
2006; Pérez Perales et al., 2012). However, there has been no consensus or standardization in this
regard.

72 The process of creating a conceptual model may be closely compared with the process of requirements elicitation for any software system. In particular, we claim that a very important 73 74 aspect of conceptual models is that they should allow their iterative, incremental and collaborative 75 construction. Indeed, agile methods in requirements engineering have demonstrated the importance of managing the inherent complexity of a system specification in an incremental and 76 77 iterative manner (Schön et al., 2017). A relevant technique to elicit requirements and get a clear 78 and complete understanding of a domain is the use of scenarios (Leite et al., 2000). The description 79 of scenarios ranges from visual (storyboards) to narrative (structured text) (Young, 2004). They 80 are constructed iteratively on the basis of a universe of discourse (UofD), i.e., a domain's 81 vocabulary or lexicon. Leite and Franco (1993) named it the language extended lexicon (LEL). It 82 is a meta-language used to gather or elicit requirements, which aims at describing the meaning of words and phrases specific to a given application domain. It has three convenient characteristics 83 84 in the context of analytical modelling: easy to learn (Cysneiros & Leite, 2001), easy to use (Gil et 85 al., 2000) and good expressiveness (Kaplan et al., 2000). Moreover, there exist specific rules to 86 derive LEL elements into scenario elements, and scenarios retrofit LEL's vocabulary in a very 87 incremental and iterative construction process (Leite et al., 2000). Here, we claim that the above 88 quality characteristics and the construction process of the pair LEL + scenarios make them an 89 adequate conceptual model from where mathematical programming models could be 90 systematically derived.

In this article, we propose a novel methodology to guide the derivation of mathematical 91 92 programming model elements from a conceptual model created with LEL + scenarios. Our derivation proposal consists of several rules that map conceptual model elements (either LEL 93 94 vocabulary items or scenario elements previously derived from LEL) into mathematical 95 programming model elements. The added benefit of this methodology is that it provides 96 traceability from vocabulary and requirements specification to each mathematical programming 97 model element. This traceability becomes very important when a change is necessary in the 98 conceptual model, to know the particular place in the mathematical programming model 99 specification where the change will have an impact.

100 In order to give further support to the derivation process, we relate conceptual model creation to a 101 knowledge building process of collective creation between stakeholders and analysts. This process 102 emphasizes the production and continuous improvement of knowledge parts (Moskaliuk et al., 103 2009), and it is usually supported with a web-based knowledge building community like a 104 mediawiki (Baraniuk et al., 2004). Thus, we have constructed a semantic mediawiki based on an 105 ontology for the collaborative creation of the conceptual model based on LEL and scenarios. 106 Moreover, the semantic mediawiki is used to semi-automatically derive mathematical 107 programming models.

108 Thus, the paper proposes a novel methodology that connects the areas of requirements engineering 109 and agile methods with conceptual modelling in order to create mathematical programming 110 models that capture the agriculture research domain more effectively and completely. 111 Summarizing, the main contributions of this paper are: (i) a proposal for utilizing the pair LEL +112 scenarios to create conceptual models that gather the vocabulary of decision makers and specify 113 the domain knowledge necessary to build a mathematical programming model; (ii) a rule-based 114 methodology for the systematic derivation of mathematical programming models from the 115 conceptual model generated by LEL + scenarios; (iii) a knowledge model designed over an

116 ontology based on the description of LEL + scenarios; and (iv) an extensible tool consisting of a 117 semantic mediawiki that allows to partially automate the mathematical modelling derivation. To the best of our knowledge, the methodology proposed in this article is the first approach to 118 119 standardize the development of a conceptual model and its consequent translation to a 120 mathematical programming model, and no other requirement elicitation method in the field of 121 software engineering has been adapted for the derivation of mathematical programming models. 122 Moreover, the derivation process provides traceability from requirements to mathematical programming model elements to deal with changes more effectively. 123

124 The rest of the paper is organized as follows. Section 2 provides a literature review on mathematical programming models, conceptual models, requirements elicitation, LEL and 125 126 scenarios and knowledge building. Section 3 describes our methodology for the systematic 127 derivation of mathematical programming model elements from the conceptual model generated 128 by LEL+ scenarios. Section 4 applies the method to derive a linear mathematical programming 129 model for fresh tomato packing. Section 5 defines an ontology for LEL + scenarios on which we 130 based the construction of a semantic mediawiki for the semi-automatic derivation of the 131 mathematical programming model. Section 6 provides conclusions and future research directions.

132 **2. Literature review**

133 **2.1 Mathematical programming models**

Mathematical programming involves finding the values of some variables that, subject to certain constraints, maximize or minimize an objective function. We assume that deterministic mathematical programming models have a generic structure: a definition part and a modelling part (Pérez et al., 2010; Shapiro, 1993). Table 1 provides a description of mathematical programming model parts.

139 **2.2 Conceptual mathematical modelling**

Siau (2004) defines conceptual modeling as the process of formally documenting a problem domain to achieve understanding and communication between the different participants. Developing conceptual models means specifying the essential objects, or components, of the system to be studied, and the relationships or types of exchanges between the objects that affect the functioning of the system (Lezoche et al., 2012). From the abstraction of conceptual models emerges the concept of reference models, which are generic conceptual models that formalize recommended practices for a given domain (Pesic & van der Aalst, 2005).

MATHEMATICAL PROGRAMMING MODEL PART	ELEMENT	DESCRIPTION	EXAMPLES
Definition part	Indexes	Objects or concepts of the model. The number of elements of a class of objects provides the number of instances of this class	Machines (m) Products (i)
	Sets	Group of instances of one or several indexes that meet certain characteristics or constraints	Group of products that can be processed by each machine $P(m)$
	Parameters	Known characteristics of one or several elements (indexes) over which is not possible to act	Capacity of each machine (Cap_m) Production cost for each product o each machine (PC_{im})
	Decision variables	Unknown characteristics of one or several elements (indexes) over which it is possible to act (decision-maker can determine their value)	Quantity to be produced of each product on each machine every time period (X_{imi})
Modelling part	Objective function	Goal/s to be optimized (minimize or maximize)	Maximize profits Minimize costs Minimize time
	Constraints	Problem limitations that should be respected for every combination of the decision variables	Availability of resources (e.g. machines' capacity) Company policies (e.g. service level Logic or implicit constraints (e.g. flow balance, positive quantities)
Decision-maker	Decision- maker	Person who makes the decision	Planner, manager
Temporal characteristics	Time-horizon	The length of time (with a beginning and end date) over which a problem is optimized	A year, six months, etc.
	Time-period	Space of time into which a time-horizon is divided	Seconds, minutes, hours, days weeks, months or years
	Replanning time period	Space of time in which the plan is calculated again	Seconds, minutes, hours, days weeks, months or years

147 **Table 1**. Mathematical programming model parts

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In the field of conceptual mathematical modelling, Schneeweiss (2003a) identifies different classes of distributed decision making (DDM) problems in supply chain management. The same author derives the coupling equations for the most usual cases in coordinating the supply chain (Schneeweiss, 2003b). However, the coupling equations are still of a very general, almost verbal character. In this context, Alemany et al. (2007) propose a reference mathematical programming 154 model for collaborative planning that addresses two of the challenges of DDM: the spatial and 155 temporal interdependencies. Alemany et al. (2011) developed an application to support the 156 integrated modelling and execution of the supply chain collaborative planning process made up of 157 several decisional centers which make decisions based on mathematical programming models. 158 However, the formulation of the own specific decisional characteristics of each decision center 159 (micro-decision view) mainly relies on the ability of the mathematical programming modeler. 160 Moreover, Pérez-Perales et al. (2012) propose a framework to support modelling the decisional 161 view of collaborative planning through mathematical programming models.

While the above studies are very useful, this article provides further tool-supported guidence and a precise specification in terms of derivation rules to derive mathematical programming models from a conceptual model, as opposed to general descriptions or relying in the modeler's ability.

165 **2.3 Process of mathematical programming model formulation**

166 Since conceptual models are not standardized, neither is the process of deriving the mathematical programming model from the concept model, which remains ad hoc. In this sense, Raghunathan 167 168 (1996) proposed a methodology to design a DSS with its underlying mathematical programming 169 and data models. The methodology includes six steps: (i) problem domain analysis, (ii) database 170 design, (iii) modelbase design, (iv) database/modelbase integration design, (v) problem/decision 171 maker characteristics and (vi) specific DSS design. However, the setting of Raghunathan (1996) 172 is a classroom, so the problem statement is completely specified from the start. Alternatively, our 173 proposal is inspired in the current, agile way of system specification, which recognizes that the 174 construction of any model should be iterative and incremental. Additionally, the use of entity-175 relationship modelling by Raghunathan (1996) has two implications: a) the problem must be 176 simple, otherwise the diagram is not even readable; and b) stakeholders may not be able to 177 understand it. Contrarily, we use a natural language and a semi-structured scenario specification

for the conceptual model, which is more appealing for a system specification that incorporatesstakeholders in the process.

180 Furthermore, Dominguez-Ballesteros et al. (2002) define different stages in the process of 181 deterministic and stochastic linear programming model formulation and implementation: 182 conceptualisation (data collection and study of the problem), data modelling (categorisation and 183 abstraction of the data), algebraic form (modeller's form), translation (matrix generator/modelling 184 language), machine-readable form (algorithm's form), solution and solution analysis. However, 185 the stages can be understood as guidelines for the mathematical programming modeler more than 186 a derivation procedure. That is, unlike Raghunathan (1996) and to the best of our knowledge, no 187 methodology or structured modeling language is proposed for the conceptualization stage.

1882.4 Requirements elicitation189

190 Requirements elicitation is the process that analysts follow to ensure a correct understanding of 191 stakeholders' needs and the domain specification before a system is designed and implemented 192 (Leite et al., 2000). In this regard, Geisser and Hildenbrand (2006) state that software requirements 193 are very complex and a multitude of stakeholders participate in their description (Geisser & 194 Hildenbrand, 2006). They propose a method called CoREA that covers collaborative requirements 195 elicitation in a distributed environment as well as quantitative decision support for distributed 196 requirements prioritization and selection. Our proposed approach also relies on collaborative 197 knowledge acquisition and description, with the added advantage of using this knowledge base as 198 a conceptual model from where a mathematical programming model can be derived through the 199 application of a set of rules.

200 Closer to our work, Laporti et al. (2009) propose an approach to develop system requirements in 201 an iterative and collaborative way. Experts in the domain collaborate to build narrative 202 descriptions of stories. Then, these stories are used as input to describe scenarios, which are in 203 turn used to define use cases. In this regard, our proposal is similar since it considers the collective 204 construction of LEL + scenarios and a mapping between LEL, scenarios and mathematical 205 programming models. The difference is that the output of the transformation in the work by Laporti 206 et al. (2009) is still a textual, semi-structured representation (use cases), which does not distance 207 much of the previous products, whereas in our case the output is a structured mathematical 208 programming model, so the mapping requires a more complex strategy that includes a precise 209 representation of the relations among model elements. Our approach uses two existing techniques 210 for requirements elicitation: the LEL (Leite & Franco, 1993) and scenarios (Leite et al., 2000). 211 The LEL is a very convenient tool for both stakeholders with no technical skills and analysts, since 212 it conforms to the mechanism used by the human brain to organize knowledge (Oliveira et al., 213 2007), which makes it easy to learn while having good expressiveness. The process to build the 214 LEL is comprised of six steps (Breitman & Leite, 2003; Kaplan et al., 2000), which allow 215 constructing a list of terms classified in four categories (see Table 2).

216 Turning into scenarios, they can be used in different stages of software development, from 217 clarifying business processes and describing requirements to providing the basis of acceptance 218 tests (Alexander & Maiden, 2004). Leite et al. (2000) propose a template with six elements to 219 describe scenarios (see Table 2), which are derived from the LEL following a methodology 220 consisting of five steps: (i) to identify main and secondary actors, i.e., LEL symbols that belong 221 to the subject type; (ii) to identify scenarios within the behavioral responses of symbols chosen as 222 actors; (iii) to define the scenario goal based on the notion of the verb symbol in which the scenario 223 is based; (iv) to identify the scenario resources, searching in the notion of the verb that created the 224 scenario, for LEL symbols of the object category; and (v) to derive episodes from each behavioral 225 response of the verb that identified the scenario.

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Category	Characteristics	Notion	Behavioral responses	
Subject	Active elements which perform actions	Characteristics or condition that subject satisfies	Actions that subject performs	
Object	Passive elements on which subjects perform actions	Characteristics or attributes that object has	Actions that are performed on object	
Verb	Actions that subjects perform on objects	Goal that verb pursues	Steps needed to complete the action	
State	Situations in which subjects and objects can be located	Situation represented	Actions that must be performed to change into another state	
Attribute	Description			
Title	Name that describes the scenar	Name that describes the scenario		
Goal	Conditions and restrictions to l	Conditions and restrictions to be reached after the execution of the scenario		
Context	Conditions and restrictions tha execution.	t are satisfied and constitute the	starting point of the scenario	
Actors	Agents that perform actions during the scenario starting from the context to reach the goal			
Resources	Products and elements used by the actors to perform actions			
Episodes	Steps executed by the actors using the resources starting at the context to reach the goal			

Table 2. LEL categories and scenarios elements.

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2.5 Ontologies and knowledge building

231 Ontologies define the common vocabulary in which shared knowledge from a domain of discourse 232 is represented (Gruber, 1993; 1995). They can be constructed in two ways, domain dependent and 233 generic. CYC (Lenat, 1995), WordNet (G.A. Miller, 1995) and Sensus (Swartout et al., 1996) are 234 examples of generic ontologies. A benefit of using a domain ontology is to attain the shared and 235 agreed definition of a semantic model of domain data and the links between different types of 236 semantic knowledge, which makes it suitable in formulating data searching strategies for 237 information retrieval (Munir & Sheraz Anjum, 2018). Furthermore, a semantic mediawiki defined over an ontology provides a web-based support for a 238 knowledge building community (Baraniuk et al., 2004). We have used a semantic mediawiki in 239

this work to allow for the collaborative definition of LEL + scenarios of the problem domain and

- for the semi-automatic derivation of the mathematical programming model using the mediawiki's
- 242 query engine.

3. Methodology for mathematical programming model derivation

244 **3.1.** Conceptual model construction and methodology overview

245 The mathematical programming model derivation process starts from an existing conceptual 246 model consisting of a complete or close to complete specification of LEL + scenarios of the 247 system. There are three variations that we propose to the original definition of LEL and scenarios 248 for the specific goal of generating mathematical programming models. The first is that we do not 249 use the terms in the "state" category of the LEL, because no mathematical programming model 250 element is derived from them. The second is that we distinguish attributes inside the notion of 251 symbols, especially those that become scenario's actors and resources. That is, an actor is a LEL 252 subject, and as such it will have a notion with its conceptual definition. We call attributes to the 253 terms that characterize the actors and appear in their notion, usually after the verb "has". Similarly, 254 a resource is a LEL object with a notion that names its attributes. In turn, attributes are also defined 255 as LEL objects, and this is the reason that attributes are underlined in the notion of the actor or 256 resource that they characterize, describing a relation between LEL terms. The third variation that 257 we propose is related to specifying the temporal location inside scenarios' context element with 258 more detail, identifying three fields: time horizon, time period and replanning time period.

259 In order to provide a better understanding of the proposed methodology, Figure 1 depicts its two 260 main stages (Conceptual model construction and Mathematical programming model construction), 261 the phases in the construction process for each stage, and two different levels of iteration. There 262 is one iteration cycle that occurs often in the construction of the conceptual model, where scenarios 263 may retrofit the LEL, and a second level or global iteration cycle, between the conceptual model 264 and the mathematical programming model, which should not be as usual. The methodology 265 provides traceability by way of rules that specify the source of each mathematical programming 266 model element. Therefore, this methodology is robust enough to actually afford changes in the 267 mathematical programming model construction.

The input for the whole process, as Figure 1 shows, is the domain knowledge obtained from stakeholders and documents. The first phase consists in the LEL specification, which is created by a system analyst together with the stakeholders and, if possible, the expert in mathematical modelling, thus creating a multi-disciplinary team. They should identify the sources of knowledge, define the LEL, verify and validate it. The second phase consists in specifying scenarios using the knowledge captured in the LEL. If during the description of the scenario, it is noticed that more knowledge from the domain is needed, the process goes back to phase 1.

275 When the knowledge captured by the LEL + scenarios appears adequate and complete, the third 276 phase (Mathematical Programming Model Derivation) begins. This phase uses the knowledge 277 captured in LEL and scenarios to derive the mathematical model. The mathematical programming 278 derivation proposal consists of several rules that map conceptual model elements (either LEL 279 vocabulary items or scenario elements previously derived from LEL) into mathematical 280 programming model elements. The derivation process may be carried out manually by the 281 mathematical programming expert, possibly together with the system analyst. In addition, we 282 provide tool support for a semi-automatic derivation through a semantic mediawiki. Even with a 283 tool support, manual revision from the mathematical programming expert will be necessary, since 284 it is not possible to automatically create the equations that model constraints from a textual description, although we can isolate the sentence that contains a constraint from the conceptual 285 286 model. In Fig. 1, the numbering of steps in the mathematical programming model derivation phase 287 denotes a sequence in which rules should be applied. Moreover, at the end of each of these steps, 288 the manual intervention of the mathematical programming expert is advised to prevent an overly 289 complex mathematical programming model (as it could happen with a large number of indexes) 290 or to spot missing items in the conceptual model. Furthermore, it could also be detected that more 291 knowledge from the LEL and Scenarios is needed, and it that case, the process goes back to the 292 conceptual model construction.

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Fig. 1. Methodology for mathematical programming model derivation.

3.2. Mathematical programming model derivation

This section presents the rules that allow deriving a mathematical programming model from a conceptual model composed of LEL + scenarios. Below we present a detailed description of each derivation rule, listed by its rule number. Note that rule numbers do not dictate an order of application except for the order dictated by the methodology and outlined in Figure 1. Following this description, Table 3 provides a summary of the rules.

303 Rule 1. The main actor of the base scenario becomes the decision maker in the mathematical

304 programming model

Main actors are those who execute actions in the **domain**, in this case, those making decisions. We consider the main actors to be a single person or several persons playing the same role, i.e., making a centralized decision. There will be a base scenario that derives from the behavioral response of the single main actor, who will be the decision maker in the mathematical programming model. Rule 2. The time period of the planning horizon defined in the temporal location, inside the
context of the base scenario, becomes an index of the mathematical programming model.
Moreover, other data objects related to time in the temporal location could also become
indexes.

The base scenario should specify the temporal location in its context attribute. Particularly, the time period specifies the regular intervals in the time horizon at which different decisions are to be made. If such time period exists, Rule 2 is applied to derive an index from it. Other LEL objects specifying time considerations (shipping day or maturity day, among others) could also appear in the temporal location and probably become indexes.

Rule 3. Scenarios' actors that have multiple instances become *indexes* of the mathematical programming model

Actors in scenarios are derived from LEL subjects. A subject in LEL could denote a specific person or a role. If it is a role, which is filled by several persons, there should be an index in the mathematical programming model to represent them. If the cardinality of a particular actor is likely to grow from 1 into several people, the mathematical programming expert could decide to include the index to make the model more flexible to accommodate this change in the near future.

326 Rule 4. Scenarios' resources that have multiple instances become indexes of the 327 mathematical programming model

Resources represent relevant physical elements or information used by scenarios' actors to achieve their goal. Resources derive from LEL's objects. Objects can be singletons (a single instance) or denote a class of elements. When an object denotes a class, it becomes an index of the mathematical programming model. Similar to Rule 3, if the object could grow into a class in the future, the mathematical programming expert could decide to include the index.

Rule 5. Actors and/or resources which are related by a notion in the LEL become *sets* in the mathematical programming model when their relation denotes a restriction

Two or more actors and/or resources are related when they appear in the same notion. In the case where the relation among them is restricted for some cases, this restriction should be defined as a set. Conversely, if the relation is many-to-many, it would not be necessary to define the sets.

Rule 6. The number of instances of the indexes could become parameters in the mathematical programming model

An actor that becomes an index derives from a LEL subject with multiple instances. The number of instances of an index is known, and therefore, it could become a parameter of the mathematical programming model, although this is not always the case. The same occurs with resources and temporal data objects. An example is the number of instances of the time period, which matches the decision time horizon and could be defined as a parameter.

345 Rule 7. Attributes of scenarios' actors and attributes of scenarios' resources and attributes 346 of their relationship with known values become parameters of the mathematical 347 programming model. Each parameter is indexed by those indexes related to it by the same 348 notion and for which its value remains known

349 In the case of attributes that did not become indexes by Rule 4 and denote a known value, by this 350 rule they become parameters of the mathematical programming model. Moreover, a parameter 351 derived by this rule should be indexed by the indexes that are related to it. We define two LEL 352 terms as related if they appear in the same notion, i.e., either one of them appears in the notion of 353 the other, or both terms appear in the notion of a third term. These indexes could include other 354 actors but also other resources. However, note that not all indexes that appear in the notion will be 355 assigned to the parameter, only those that refer to a known value. Thus, the mathematical 356 programming expert should determine which subset of indexes refers to a known value, and the

parameter should be indexed only by that subset of indexes. The notion gives the whole subset,but the expert decides what indexes should be used.

Rule 8. Attributes of scenarios' actors and attributes of scenarios' resources and attributes of their relationship that have unknown values become decision variables of the mathematical programming model. Each decision variable is indexed by those indexes related to it by the same notion and for which its value is unknown

This rule is similar to Rule 7 but for unknown values. That is, attributes that appear in the notion of actors or resources, which values should be assigned in the decision process, become decision variables. Moreover, decision variables should take the indexes that are related to it by the same notion and refer to unknown values. It could be necessary to define artificial decision variables (without economic/physical interpretation) in order to mathematically represent a reality or to force some logical constraint.

369 Rule 9. The goal of the base scenario contains the objective function

The base scenario should specify in its goal attribute, the purpose of the main actor (which becomes the decision maker by Rule 1) in executing the scenario. This goal is specified as a complex sentence with a relative clause that starts with "so as to" followed by the verb "minimize" or "maximize". From this verb to the end, this relative clause becomes the objective function. Moreover, the expert may look for further details of each objective function in the notion of the LEL symbols involved in the goal.

Rule 10. The set of context sentences of all scenarios become the set of constraints of the mathematical programming model

378 Scenarios should specify in its context attribute, the conditions to comply. These conditions are379 described in natural language, as sentences that relate to the actors and resources of each scenario.

380 Experts in mathematical programming modeling should use the restrictions described in the 381 scenarios' context and relate them to parameters and indexes previously defined by other rules to 382 derive the set of mathematical programming model constraints. These constraints usually contain 383 logical constraints that represent business rules. These rules should appear during the requirements 384 elicitation that a system analyst carries out to construct the LEL, and therefore they would also be 385 derived as part of the scenarios' context. Additionally, there are added other artificial constraints 386 (for instance, a positive boundary to variables) in order to avoid erroneous results. These 387 constraints will not generally appear in the conceptual model and they should be added by a 388 subsequent analysis of the mathematical programming expert.

Table 4 summarizes the relationship among LEL, scenarios and mathematical programming model elements. Rules are grouped by the mathematical programming model element that is derived from them. The second and third columns use indentation to represent nested concepts (for example, in Rule #2, the scenario element that generates an "Index" is the "Time period", inside the "Temporal

393 location", which is in the "Context" of the "Base scenario").

Rule Number	LEL model	Scenario model	Mathematical model
1	Subject	Base scenario Main actor	Decision Maker
2	Object	Base scenario Context Temporal location Time period	Index
3	Subject (multiple instances or single instanceopt)	Any scenario Actor	Index
4	Object (multiple instances or single instanceopt)	Any scenario Resource	Index
5	Subject / Object Notion (restriction)	Any scenario Actor / Resource	Set
6	Subject / Object Notion (no. of instances)	Any scenario Actor / Resource (index)	Parameter
7	Subject / Object Attribute (known value)	Any scenario Actor / Resource	Parameter

Table 3. Equivalences among LEL, scenario and mathematical programming model elements.

		Attribute	
8	Subject / Object Attribute (unknown value)	Any scenario Actor / Resource Attribute	Decision Variable
9	Subject Behavioral response (verb)	Base scenario Goal	Objective function
10	Object	Any context	Constraint

395 **4.** Application

396 This section applies the above methodology to the problem of fresh tomato packing addressed by

397 Miller et al. (1997). The purpose of using an existing problem is to contrast the result of our

398 derivation rules with a real, published mathematical programming model while avoiding the long

399 description that a new mathematical program would require.

400 **4.1 Conceptual model of the tomato packing problem: LEL + scenarios**

401 This section presents the conceptual model for the tomato packing problem created in terms of

402 LEL + scenarios. The team assembled for this task was multidisciplinary, that is, composed of

403 system analysts and a mathematical programming expert. The information sources of the UofD to

404 construct the LEL were provided by the article from Miller et al. (1997), interviews with local

405 tomato producers that played the role of customers and other documentation sources online. After

406 three iterations, the team arrived at the LEL that appears in Table 4.

407 **Table 4.** LEL of the tomato packing problem.

Term	Role	Notion
Packinghouse management (PM)	Subject	Conducts the business of the packinghouse. The PM decides when to harvest tomatoes matured in the present or previous cycle, communicates its decision to growers and packs the harvested tomatoes to fulfil the market demand
Grower	Subject	Person responsible for a tomato field (has been assigned a certain number of acres of tomatoes), including harvesting the tomatoes, for which it has some harvest capacity. There are several growers. Each grower produces a certain yield of bins of tomatoes per acre to take them to the packinghouse
Market	Subject	Customers of the packinghouse, who buy tomatoes to sell them. The market has a market demand in number of boxes of tomatoes they would like to buy each day
Acres of tomatoes	Object	Land assigned to a grower with tomatoes that get matured on a certain maturity day, and are harvested on a certain harvesting day. Acres may have a fraction of "vine ripe tomatoes" that are sold "as is"
Tomato	Object	Produce planted by growers on the acres of their fields. Tomatoes that have not been harvested in 2 cycles generate a cost of damaged tomato
Harvesting day	Object	Day in which tomatoes already matured are harvested. Every day in the horizon may be a harvesting day
Maturity day	Object	Day in a period in which tomatoes in an acre get ready to be harvested. The acres of a specific grower may have different maturity days within the decision horizon

Decision horizon	Object	Largest time in which the readiness of tomato fields for harvest can be accurately predicted. It is 3 days
Harvest capacity	Object	The capacity of a grower to harvest during a certain day
Bin	Object	Container where the grower places the harvested tomatoes
Cost of damaged tomato	Object	Penalty cost due to dissatisfaction of a grower because of delayed harvest of fields matured in the previous and present cycles in \$ per bin
Fraction of "vine ripe tomatoes" (v.r.t.)	Object	Tomatoes sold without gassing
Yield of bins of tomatoes	Object	The number of bins of harvested tomatoes per acre of a certain grower
per acre	01	
Packinghouse	Object	Place where tomatoes are packed in boxes and stored. It has a packing capacity, and a gassing capacity per day. The packinghouse requires some fraction of hour needed to pack a bin at a certain packing cost. The packinghouse generates a fraction of tomatoes ready after gassing. The packinghouse works on regular hours (9 to 5) and overtime hours (after 5pm) to generate an inventory level at the end of the day
Packing cost	Object	The total packing cost consist of: (1) cost of damaged tomatoes; (2) inventory holding cost, (3) shortfall cost, (4) overtime and (5) regular hour packing costs
Packing capacity	Object	No more tomatoes may be packed once the packinghouse reaches the packing capacity
Gassing capacity	Object	Capacity of the packinghouse to gass tomatoes in a harvesting day. It is measured in number of boxes of tomatoes
Fraction of hour needed to pack a bin	Object	Time required for packing 1 bin of harvested tomatoes and put them in boxes
Fraction of tomatoes ready after gassing	Object	Tomatoes ready after a gassing session
Regular packing hours	Object	Hours when the packinghouse is operating on a day, that generates a regular packing cost. It goes from 9 am to 5 pm
Overtime packing hours	Object	Extra hours required to complete the packing at the packinghouse on a day. They generate a higher cost than the regular packing hours. Overtime hours are after 5pm
Regular packing cost	Object	Cost of packinghouse operation in \$ per hour during regular packing hours
Overtime packing cost	Object	Cost of packinghouse operation in \$ per hour during overtime packing hours
Inventory level	Object	Number of boxes of tomatoes of the packinghouse at the end of a certain day. It has a certain inventory holding cost in box/day
Inventory holding cost	Object	Cost of packinghouse storage in boxes/day
Market demand	Object	Number of boxes of tomatoes that the packinghouse customers require in each harvesting day. If the market demand is not covered it generates a shortfall
Shortfall	Object	Number of missing boxes of tomatoes needed to reach the market demand on a certain harvesting day
Shortfall cost	Object	Cost of being short on satisfying the market demand in \$ per box short
Box	Object	Container where tomatoes are placed during packing
Harvest	Verb	To cut the tomatoes that are matured
Pack	Verb	Put in boxes the harvested tomatoes. Packing is done on regular hours at a certain cost or overtime hours to complete packing all harvested tomatoes
Gass	Verb	Technique used to ripen tomatoes that are not completely matured by exposing them to ethylene gas

409 The first version of the scenarios was created after the first iteration of the LEL and was used to

410 retrofit the second iteration of the LEL.

411 The following four tables describe the scenarios of the tomato packing problem. First, Table 5

412 presents the sole Level 0 scenario, called *base scenario*. Then, Tables 6 through 8 show the three

413 scenarios of Level 1, which derive from episodes of the base scenario.

414

Scenario 0:	Plan the harvest and	I the packing of fresh tomatoes
Goal	Make a plan at the b	eginning of the present cycle to harvest and pack tomatoes matured on the present and last
	cycles, so as to minin	nize the total packing cost
Actors	Main actor	Packinghouse management (PM)
	Secondary actors	Growers, market
Resources	Physical resources	Packinghouse; acres of matured tomatoes for each grower in the present and past cycles;
		tomatoes; bins; boxes.
	Information	Market demand in number of boxes for each day in the present cycle; for each grower, the
	resources	number of acres of matured tomatoes in the present and past cycles and the number of bins
		of tomatoes generated after harvesting.
Context	- Not all tomatoes that	t get matured in a cycle are harvested in the same cycle.
	- Tomatoes harvested	in the next cycle after they get matured may be sold but have less quality.
	- Tomatoes not harve	sted in the next cycle after they get matured must be discarded.
	- A grower may only	harvest up to their capacity.
	- The packinghouse n	nay only pack and gass a limited number of tomato boxes a day.
	- Temporal location:	
	 Decision horizon 	: 3 days
	• Decision period:	harvesting day; every day in a decision horizon.
	• Other temporal va	ariables: maturity day; any day in the decision horizon.
Episodes	- PM makes a plan wi	th the harvesting day of matured tomatoes, for each day in the present cycle, in number of acres
	for each grower.	
	- Each grower harves	ts the amount decided and communicated by the PM.
	- Each grower takes t	he harvested tomatoes in bins to the packinghouse.
	- PM packs the harves	sted tomatoes in the packinghouse, labelling some boxes as "vine-ripe tomatoes".
	- PM gasses all boxes	of tomatoes which are not labelled as "vine ripe".
	- Tomato boxes are sl	nipped to cover the market demand, and the surplus remains as inventory of the packinghouse.

Table 5. Scenario Level 0 of the tomato packing problem.

Table 6. Scenario 1.1 at Level 1 of the tomato packing problem.

Scenario 1.1:	Plan the the harvest	ing day of matured tomatoes	
Goal	Decide how many acr	res of matured tomatoes to harvest for each grower in each day of the present cycle	
Actors	Main actor	Packinghouse management (PM)	
Resources	Physical resources	Acres of tomatoes.	
	Information resources	For each grower: harvest capacity, acres of matured tomatoes for each day and yields of bins of tomatoes per acre. Also: cost of tomatoes damaged due to delayed harvest, packing and gassing capacity of the packing house.	
Context	- A grower may only harvest in a day up to their harvest capacity.		
	- The number of bins of harvested tomatoes to pack from all growers should be less than the available gassing capacity of the packinghouse for that day.		
	- The number of bins of harvested tomatoes to be packed per day should be less than the combined regular and overtime packing capacity of the packinghouse.		
Episodes	- Considering the info grower, the number o	rmation resources available, the PM calculates, for each day in the present cycle and for each f acres to harvest of tomatoes matured of the previous and the present cycles.	

Table 7. Scenario 1.2 at Level 1 of the tomato packing problem.

Harvest	
Harvest the tomatoes	and take them to the packinghouse.
Main actor	Grower
Physical resources	Acres of tomatoes; tomatoes; bins; packinghouse.
Information	Harvest capacity; acres of matured tomatoes for each day; number of acres to harvest each
resources	day
- Tomatoes to be harv	rested are matured.
- The grower cuts the	tomatoes from the acres already matured that the PM decided to cut on the present day.
- The grower places th	ne tomatoes in bins.
- The grower takes the	e bins to the packinghouse.
	Harvest Harvest the tomatoes Main actor Physical resources Information resources - Tomatoes to be harv - The grower cuts the - The grower places th - The grower takes the

Scenario 1.3:	Pack the harvested tomatoes		
Goal	Put the tomatoes in bo	xes to be transported.	
Actors	Main actors	Packinghouse personnel	
Resources	Physical resources	Bins of tomatoes; boxes; packinghouse.	
_	Information	Gassing capacity; regular packing hours; regular packing hour cost; overtime packing hours;	
	resources	overtime packing hour cost	
Context	- Packing occurs during regular packing hour plus overtime packing hours, which combined are at most 12 hours.		
	- Regular packing hour	rs are at most 8 hours a day, and overtime packing hours are at most 4 hours a day.	
	- No more tomatoes m	ay be packed once the packinghouse reaches the packing capacity	

419 **Table 8.** Scenario 1.3 at Level 1 of the tomato packing problem.

421 **4.2 Derived mathematical programming model**

422 We show the derived mathematical programming model elements in separate tables according to

423 the rules applied. First, Table 9 shows the decision maker and indexes generated by applying Rules

- 424 1-4.
- 425 **Table 9.** Derivation of decision maker and indexes.

Rule Number	LEL model	Scenario model	Mathematical programming model
1	Subject: Packinghouse Management (PM)	Scenario 0 Main actor PM	Decision Maker PM
2	Object: Harvesting day	Scenario 0 Context Temporal location Decision period	Indexes t
2	Object: Maturity day	Scenario 0 Context Temporal location Other temporal vars	j
3	Subject: Grower	Scenario 0 and 1.2 Actor: Grower	i

⁴²⁶

427 In the process of deriving the indexes, some scenarios' resources with multiple instances were 428 considered as candidates on which to apply Rule 4. After that, the expert reviewed the relations 429 among actors and resources but did not derive any sets because there are none restricted relations. 430 Applying Rule 6 to the number of instances of the index for time period t yielded the time horizon 431 as the parameter T. The number of instances of the index for maturity day *j* is the same parameter 432 T. The number of instances of the index for grower *i* yielded parameter K. Other parameters came 433 from analyzing the attributes of scenarios' actors and resources. For example, the attribute acres 434 of actor grower yielded parameter H. Rule 7 indicates that H should be indexed by the indexes "related to it by the same notion". In this case, the expert inspected the notion of acres looking the underlined terms (i.e., related elements) that were defined as indexes: *i* for "grower", *j* for "maturity day" and *t* for "harvesting time". However, the known values of acres are their grower and their maturity day, but their harvesting time is unknown. Therefore, the indexes assigned to the parameter are *i* and *j*, and the parameter is H_{ij} . Other parameters were derived similarly. The whole list of parameters appears in Table 10.

Rule Number	LEL model	Scenario model	Mathematical programming model parameter
6	Object: Harvesting day Index: t	Scenario 0 Context Temporal location Decision period	T
6	Subject: Grower Index: <i>i</i>	Scenario 0 and 1.2 Actor: Grower	K
7	Subject: Grower Attribute: Acres Related indexes: Grower (<i>i</i>), Maturity day (<i>j</i>)	Scenario 0 and 1.2 Actor: Grower Attribute: Acres	H_{ij}
7	Subject: Grower Attr: Harvest capacity Related indexes: <i>i</i>	Scenario 0 and 1.2 Actor: Grower Attr: Harvest capacity	Ui
7	Subject: Grower Attr: Yields of bins Related indexes: <i>i</i>	Scenario 0 and 1.2 Actor: Grower Attr: Yields of bins	bi
7	Subject: Market Attr: Market demand Related indexes: Harvesting day (t)	Scenario 0 Actor: Market Attr: Market demand	D _t
7	Object: Acres Attr: Fraction of v.r.t. Related indexes: -	Scenario 0 Resource: Acres Attr: Fraction of v.r.t.	δ
7	Object: Packinghouse Attr: Packing capacity Related indexes: -	Scenario 0 Resource: Packinghouse Attr: Packing capacity	Р
7	Object: Packinghouse Attr: Gassing capacity Related indexes: t	Scenario 0 Resource: Packinghouse Attr: Gassing capacity	G_t
7	Object: Packinghouse Attr: Packing cost Notion: Cost of damaged tomato Related indexes: -	Scenario 1.3 Resource: Packinghouse Attr: Packing cost Notion: Cost of damaged tomato	С
7	Object: Packinghouse Attr: Packing cost Notion: Inventory holding cost Related indexes: -	Scenario 1.3 Resource: Packinghouse Attr: Packing cost Notion: Inventory holding cost	Ch

441 **Table 10**. Derivation of parameters.

7	Object: Packinghouse	Scenario 1.3	Cs
	Attr: Packing cost	Resource: Packinghouse	
	Notion: Shortfall cost	Attr: Packing cost	
	Related indexes: -	Notion: Shortfall cost	
7	Object: Packinghouse	Scenario 1.3	Cr
	Attr: Packing cost	Resource: Packinghouse	
	Notion: Regular	Attr: Packing cost	
	packing cost	Notion: Regular	
	Related indexes: -	packing cost	
7	Object: Packinghouse	Scenario 1.3	Со
	Attr: Packing cost	Resource: Packinghouse	
	Notion: Overtime	Attr: Packing cost	
	packing cost	Notion: Overtime	
	Related indexes: -	packing cost	
7	Object: Packinghouse	Scenario 0	f
	Attr: Fraction of hour	Resource: Packinghouse	·
	needed to pack a bin	Attr: Fraction of hour	
	Related indexes: -	needed to pack a bin	
7	Object: Packinghouse	Scenario 0	α
	Attr: Fraction of tom.	Resource: Packinghouse	
	ready after gassing	Attr: Fraction of tom.	
	Related indexes: -	ready after gassing	

The next step was to derive the decision variables from the analysis of the attributes of scenarios' 443 444 actors and resources, but this time, with unknown values. For example, the attribute acres of actor 445 grower, with a certain maturity day and with an uncertain harvesting day. This attribute yielded decision variable X. Similar to the case for parameter H, to find the indexes for variable X the 446 447 expert looked at the underlined indexes in notion of acres, which are: *i* for grower, *j* for maturity day and t for harvesting time, and the 3 of them are assigned to X to yield X_{ijt} . Other decision 448 449 variables were derived similarly by applying Rule 8 (I_t , R_t , O_t , S_t), and appear in Table 11. Further analysis on the scenarios and the context, caused the expert to split the decision variable X_{ijt} in 2 450 451 variables: X_{ijt} to refer to the acres matured on the present cycle and L_{ijt} to refer to the acres matured 452 on the last cycle. Additionally, 2 more decision variables were needed to represent the acres not 453 harvested, both in the present cycle (Y_{ijt}) and the past cycle (A_{ijt}) . 454 To define the objective function¹, Rule 9 was applied. Then, the expert had to manually write the

455 final equation:

456 Minimize

457
$$\sum_{i=1}^{K} \sum_{j=1}^{T} \sum_{t=1}^{T} C * (A_{ijt} + Y_{ijt}) + \sum_{t=1}^{T} Ch * I_t + \sum_{t=1}^{T} Cs * S_t + \sum_{t=1}^{T} Cr * R_t + \sum_{t=1}^{T} Co * O_t$$

459 **Table 11**. Resulting decision variables.

Rule	LEL model	Scenario model	Mathematical programming model
8	Subject: Grower Attribute: Acres Rel. indexes: <i>i</i> , <i>j</i> , <i>t</i>	Scenario 0 and 1.2 Actor: Grower Attr.: Acres	X_{ijt}
8	Object: Packinghouse Attr.: Inventory level Related indexes: <i>t</i>	Scenario 0 Resource: Packinghouse Attr.: Inventory level	It
8	Object: Packinghouse Attr.: Regular packing hours Related indexes: t	Scenario 0 Resource: Packinghouse Attr.: Regular packing hs	R _t
8	Object: Packinghouse Attr.: Overtime packing hours Related indexes: t	Scenario 0 Resource: Packinghouse Attr.: Overtime packing hs	<i>O</i> _t
8	Object: Market demand Attribute: Shortfall Related indexes: <i>t</i>	Scenario 0 Resource: Market demand Attribute: Shortfall	S _t
-	Derived manually by the expert	Scenario 0 and 1.2 Actor: Grower. Attr.: Acres (matured on <i>last</i> cycle)	L _{ijt}
-	Derived manually by the expert	Scenario 0 and 1.2 Actor: Grower. Attr.: Acres (matured <i>present</i> cycle <i>not</i> harvested)	Y _{ijt}
-	Derived manually by the expert	Scenario 0 and 1.2 Actor: Grower. Attr.: Acres (matured on <i>last</i> cycle <i>not</i> harvested)	A_{ijt}

460

461 Deriving the constraints was mostly handcrafted taking all the information available in the context

462 sentences of scenarios to create the corresponding equations, plus the addition new constraints to

463 balance quantities and make the mathematical programming model work. Constraints appear in

- 464 Table 12.
- 465 **Table 12**. Resulting constraints.

Rule	Scenario model	Mathematical programming model
10	Scenario 0 & 1.1 Context sentence: A grower may only harvest in a day up to his harvest capacity.	$\sum_{i=1}^{K} X_{ijt} + L_{ijt} \le U_i \forall_{it}$
10	Scenario 1.1 Context sntc: The number of bins of harvested tomatoes to pack from all growers should be less than the gassing capacity of the packinghouse for that day.	$(1 - \delta) \sum_{i=1}^{K} \sum_{t-j=0}^{T-1} X_{ijt} * b_i + \sum_{i=1}^{K} \sum_{t+T-j=1}^{T} L_{ijt} * b_i \le G_t \forall_t$
10	Scenario 1.1 Context sntc: The number of bins of harvested tomatoes to be packed per day should be less than the combined regular and overtime packing capacity of the packinghouse.	$O_t + R_t - f \sum_{i=1}^{K} \sum_{t=j=0}^{T-1} X_{ijt} * b_i - f \sum_{i=1}^{K} \sum_{T-j=1}^{T} L_{ijt} * b_i = 0 \forall_t$

24

(1)

10	Scenario 1.3 Context sntc: Packing occurs during regular packing hour plus overtime packing hours, which are at most 12 hours.	$O_t + R_t \le 12 \ \forall_t$
10	Scenario 1.3 Context sntc: Regular packing hs. are at most 8 hours/day	$R_t \leq 8 \; \forall_t$
-	Added by expert: balance the acres matured in the previous cycle but not yet harvested	$A_{ijt} - A_{ijt-1} + L_{ijt} = 0 \; \forall_{ijt}$
-	Added by expert: balance the acres matured in the present cycle but not yet harvested	$Y_{ijt} - Y_{ijt-1} + X_{ijt} = H_{ij} \forall_{ijt}$
-	Added by expert: balance the end-of-period inventory level (equal to the preceding end-of-period level + the quantity of "vine ripe" tomatoes packed + the number of boxes of tomatoes ready after gassing - the forecasted demand)	$I_{t} - S_{t} - I_{t-1} + S_{t-1} - \delta \sum_{i=1}^{K} \sum_{t-j=0}^{T-1} X_{ijt} * b_{i} + \delta \sum_{i=1}^{K} \sum_{t-T-j=1}^{T} L_{ijt} * b_{i} = D_{t} + G_{t} \forall_{t}$
-	Added by expert: assure a continual flow of tomatoes to the market. The mature green tomatoes to be packed should be at least equal to a fraction α of tomatoes ready on the day of gassing.	$(1 - \delta) \sum_{i=1}^{K} \sum_{t-j=0}^{T-1} X_{ijt} * b_i + \sum_{i=1}^{K} \sum_{t+T-j=1}^{T} L_{ijt} * b_i \ge \alpha G_t \forall_t$

466 5. Semantic mediawiki construction for the LEL and scenarios definition

A domain ontology is proposed to attain the shared and agreed definition of a semantic model for the LEL and scenarios. Moreover, ontology-based information retrieval allows us to formulate queries based on our derivation rules, which will help in the semi-automatic derivation of mathematical programming model elements. Finally, tool support is provided through a semantic mediawiki constructed over the ontology, which allows for the knowledge building process of a conceptual model and its derivation into math model elements.

473 **5.1 Ontology Model**

474 The proposed ontology is depicted in Figure 2. Thus, Subjects symbols are related to Scenario's 475 Actors while Objects symbols are related to Scenario's Resources. Moreover, Verbs symbols are related to Scenario and Episode from Scenario's representation as they represent the activities or 476 477 actions that are realized. LEL symbols are represented by the Symbol element, that has two 478 properties: a notion and a list of behavioral responses. Thus, the notion property just contains has 479 relations with Subjects and Objects that represent attributes of the described Symbol. Since we 480 need to differentiate known attributes (parameters) from unknown ones (decision variables), the 481 has relation is in fact modeled as two separate relations: has known and has unknown. In turn, the *behavioral response* of a LEL's Symbol is represented using a relation to the *Verbs* that represent
the actions were the Symbol participates, and therefore, its responsibilities.

484 From the scenario's perspective, the element *Scenario* is represented by a property to define a *title* 485 as plane text. The rest of the Scenario's properties are represented as relations with other model 486 elements. Thus, there is a relation called *bounded* to a *Context*. There are two relations from 487 Scenario to the Actor element called involves main actor and involves secondary actor, to 488 represent the main and secondary actors of the Scenario respectively. Scenario also has a property 489 called executed over, to related it with the Resources over which it is executed. The Scenario's 490 episodes are described by the property *performs* related with the *Episode* elements. Finally, 491 Scenarios are connected by the property has to the Goal element.

492 In turn, a *Context* has a text property *description* and a *has* property related to a *TemporalLoc* that 493 represents the temporal location of the scenarios with its properties for time-horizon, time period 494 and replanning time period. The Actor element has name and instance number as properties, 495 where the latter is used for the mathematical programming model derivation, to identify actors 496 with more than one instance as indexes. *Resource* has a structure identical to *Actor* although their 497 semantic meaning is completely different. The *Episode* element has a *sentence* that describes it 498 and a relation *described in* that connects the Episodes to the parent Scenario. Moreover, a *Goal* 499 has a property description and a relation optimize to an Optimization Goal. This Optimization 500 Goal is not part of the original definition of scenarios but added for mathematical programming 501 model derivation purposes. It is described by two properties: Operation and TargetVariable to 502 define the max/min operation for one particular variable as objective of the Scenario's Goal. 503 Finally, there is a Constraint element that could be related with Episode, Actor, Resource or 504 TemporalLoc elements by the property is restricted by. A Constraint is defined by the property 505 *expression*, which is applied on the corresponding elements.



506 507 **Fig. 2.** The LEL and scenarios ontology.

508

509 5.2 Semantic queries

510 The queries rely on the definition of a specific Scenario instance defined as Base Scenario. The

511 result of these queries will be used by the mathematical programming expert to obtain a

512 preliminary version of the final mathematical programming model, as explained before. Table 13

513 summarizes the queries, in a pseudo-code that makes them more readable.

Rule Number	Mathematical model output	Semantic Query
1	Decision Maker	Base Scenario involves main actor: ?Actor
2	Index	Base Scenario bounded: ?Context ?Context has: ?TemporalLoc ?time period ?Context ?Context
3	Index	Scenario involves main actor: ?Actor ?Actor instance_number >1: ?Actor
		Scenario involves secondary actor: ?Actor ?Actor instance_number >1: ?Actor
4	Index	Scenario executed over: ?Resource ?Resource instance_number > 1: ?Resource
5	Set	Symbol has known: ?Attribute1 Symbol has known: ?Attribute2 (?Attribute1 is restricted by: ?Constraint) == (?Attribute2 is restricted by: ?Constraint) ?Attribute1, ?Attribute2
6	Parameter	Scenario executed over: ?Resource ?Resource instance_number > 1: ?Resource instance_number
		Scenario involves secondary actor: ?Actor ?Actor instance_number > 1: ?Actor instance_number

514 **Table 13.** Queries based on each rule to derive potential mathematical programming model elements

7	Parameter	(Actor has known: ?Attribute)+ (Resource has known: ?Attribute)
8	Decision Variable	(Actor has unknown: ?Attribute)+ (Resource has unknown: ?Attribute)
9	Objective function	Base Scenario has: ?Goal ?Goal optimize: ?Optimization Goal
10	Constraint	Constraint

517 Rule 1 determines the decision maker by requesting the main Actor from the Base Scenario. Rule 518 2 determines the temporal index from the time period, accessing the Context of the Base Scenario 519 through the bounded property, and from the Context, using the properties has to reach the 520 properties of the *Temporal Location*. Rules 3 and 4 are also intended for deriving indexes. In these 521 queries, all the instances of *Actor* and *Resource* in all the scenarios are collected by the properties 522 involves main actor, involves secondary actor and executed over, and they are selected if the 523 property instance number is greater than 1. Rule 5 determines relations among Actors and 524 Resources that are candidates to become sets, specifically, if they appear in the same notion and 525 are related with the same *Constraint* by the property *is restricted by*. Rule 6 derives parameters 526 from the indexes obtained by rules 3 and 4, specifically, the number of instances described by the 527 property instance number. Rule 7 derives parameters from known Attributes of Actors and 528 Resources. Particularly, this rule uses the property has known that belongs to Symbol elements 529 representing Subjects (for Actors) and Objects (for Resources). Similarly, Rule 8 determines 530 decision variables but using the property has unknown to denote the unknown Attributes. To define 531 the optimization goal of the mathematical programming model, it is necessary to access to the 532 Goal of the Base Scenario by the property has and subsequently, to its Optimization Goals by the 533 property optimize. Finally, any other restriction for the model could be derived from the Constraint 534 elements.

535 **5.3 Mediawiki implementation**

We have built a semantic mediawiki in order to provide support for the collaborative construction of a knowledge base. The wiki provides the capability of creating and editing articles by way of a user-friendly interface guided by forms that will be used by stakeholders, analysts and mathematical modelling experts. These forms are based on the ontology proposed for the LEL and scenarios. Figure 3 shows a form to describe a Scenario. The figure shows that some attributes as goal and context are plain text, while others are described with a kind of button or *token*. These tokens describe relations to other elements of the model already created.

Edit Scenario: Plan the harvest and the packing of fresh tomatoes

Goal:	Minimize the total packing cost	
Context:	Temporal location: * Decision horizon: 3 days * Decision period: harvesting day; every day in a decision horizon. * Other temporal variables: maturity day; any day in the decision horizon.	(1)
Main Actor:	× Packinghouse management	
Secondary Actors:	× Grower	
Resources:	× Acres × Tomatoes × Bins × Boxes	
Episodes:	Fach grower takes the harvested tomatoes in bins to the packinghouse.	
Exceptions:	🛛 🛪 A grower may only harvest in a day up to his harvest capacity.	
	* The number of bins of harvested tomatoes to pack from all growers should be less than the gassing capacity of the packinghouse for	or that day.

543

544 **Fig. 3**. Mediawiki form based on LEL and scenarios' ontology.

545

- 546 In turn, Figure 4 shows a form to navigate a Scenario. The wiki-links could be blue or red
- 547 describing whether the related article is already defined or not, respectively.

Plan the harvest and the packing of fresh tomatoes

1 Goal		
2 Context		
3 Actors		
4 Resources		
5 Episodes		
6 Exceptions		
GOdI [edit source]		
Minimize the total pac	king cost	
Minimize the total pac	king cost ce]	
Minimize the total pac Context [edit sour Temporal location: De	king cost ce] cision horizon: 3 days	
Minimize the total pac Context [edit sour Temporal location: De Actors [edit source	king cost ce] cision horizon: 3 days e]	
Minimize the total pac Context [edit sour Temporal location: De Actors [edit sourc Main Actor	king cost ce] cision horizon: 3 days 9] Packinghouse management	
Minimize the total pac Context [edit sour Temporal location: De Actors [edit sourc Main Actor Secondary Actors	king cost ce] cision horizon: 3 days e] Packinghouse management Grower	
Minimize the total pace Context [edit source Temporal location: De Actors [edit source Main Actor Secondary Actors Resources [edit sources]	king cost ce] cision horizon: 3 days a] Packinghouse management Grower	

548 549

Fig. 4. Scenario's article.

550

551 Finally, the capability of application of ontologies as a semantic knowledge model allows to 552 implement the semantic queries described previously to semi-automatically derive mathematical 553 programming model elements from LEL + scenarios elements. Thus, once the knowledge base is 554 constructed, the mathematical modelling expert will be able to generate new articles with a 555 preliminary version of the mathematical programming model. Figures 5 displays an example, with 556 the article generated from the LEL and scenarios of the case study. Note that the support is not 557 completely automatic because the inference only allows for an approximation to the mathematical programming model, and the expert is still needed to verify the correctness of the mediawiki 558 559 derivation and provide the algebraic form.

	e management
Objective	function [edit edit source]
Description: N	Vinimize the total packing cost.
Type: Minimi	zation
Objective var	iable: Packing cost
Indexes [edit edit source]
By rule 2	[edit edit source]
 Harvesting 	g day
 Maturity d 	lay
By rule 3	[edit edit source]
 Grower 	
Bv rule 4	[edit edit source]
Acres	
 Tomatoes 	
• Bins	
 Boxes 	
Sets [edit	edit source]
Constrain	
A grower	anis expressions. [edit[edit[source]]
The numb	may only harvest in a day up to his harvest capacity. ier of bins of harvested tomatoes to pack from all growers should be less than the gassing capacity of the packinghouse for that day.
The numb The numb	may only harvest in a day up to his harvest capacity. Her of bins of harvested tomatoes to pack from all growers should be less than the gassing capacity of the packinghouse for that day. Her of bins of harvested tomatoes to be packed per day should be less than the combined regular and overtime packing capacity of the packinghouse.
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564 6. Conclusions

This paper has presented a novel methodology that connects the areas of requirements engineering 565 with conceptual modelling in order to build mathematical programming models that capture the 566 business domain more effectively and completely. Specifically, the methodology has proposed for 567 the first time the use of the LEL and scenarios for creating a conceptual model of a domain from 568

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569 where a mathematical programming model can be derived. The construction of the conceptual 570 model invites the participation of all stakeholders, which is deficiency of other proposals for DSS 571 construction in agriculture. In comparison with other approaches for conceptual mathematical 572 modelling, this article provides further tool-supported guidence about how to obtain the problem 573 definition and how to derive a mathematical programming model from a precise specification in 574 terms of derivation rules, as opposed to relying on mere textual descriptions or in the modeler's 575 ability. Moreover, we have proposed an ontology that provides the basis for a semantic mediawiki 576 that serves both, sharing knowledge of the conceptual domain model among the different 577 stakeholders, as well as semi-automating the derivation of the mathematical programming model. 578 The usefulness of this proposal can be understood from several perspectives: research, academic 579 and managerial. From the research and academic points of view, we may highlight the main 580 contributions as follows: (i) it provides a novel step-by-step methodology based on the LEL and 581 scenarios that allows both: to obtain the required information to derive the definition part of a 582 mathematical programming model, and to define the optimization problems that constitute the 583 modelling part of the model; (ii) our approach provides a structure to the problem that allows to 584 identify the elements of the problem clearly; (iii) using the LEL and scenarios to create a 585 conceptual model iteratively and incrementally in collaboration with stakeholders allows applying 586 an agile development approach to mathematical modelling; (iv) the use of LEL and scenarios 587 provides traceability from the requirements to the mathematical programming model 588 implementation to cope with possible changes of requirements and a better understanding of their 589 impact on the model; and (v) the process of creating a conceptual model with LEL + scenarios 590 also generates a complete specification of requirements for a potential model-based DSS. 591 Regarding the managerial perspective, we believe that the ease of use and good expressiveness of 592 the proposed methodology will facilitate the implementation of mathematical programming 593 models in agriculture, as well as provide new tools for teaching mathematical programming and

- 594 foster research in the combined areas of agile methods in requirements engineering, mathematical
- 595 programming and decision support system development. Further research includes validating the
- 596 proposed methodology in real world case studies from agriculture. Finally, we intend to extend
- 597 the approach to the derivation of mathematical programming models under uncertainty, such as
- 598 stochastic programming and fuzzy mathematical programming.
- 599 Acknowledgments. This work was supported by the European Commission, project H2020-600 RUC-APS, grant number H2020-MSCA-RISE-2015-691249; and the Argentinian National 601 Agency for Scientific and Technical Promotion (ANPCyT), grant number PICT-2015-3000.

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