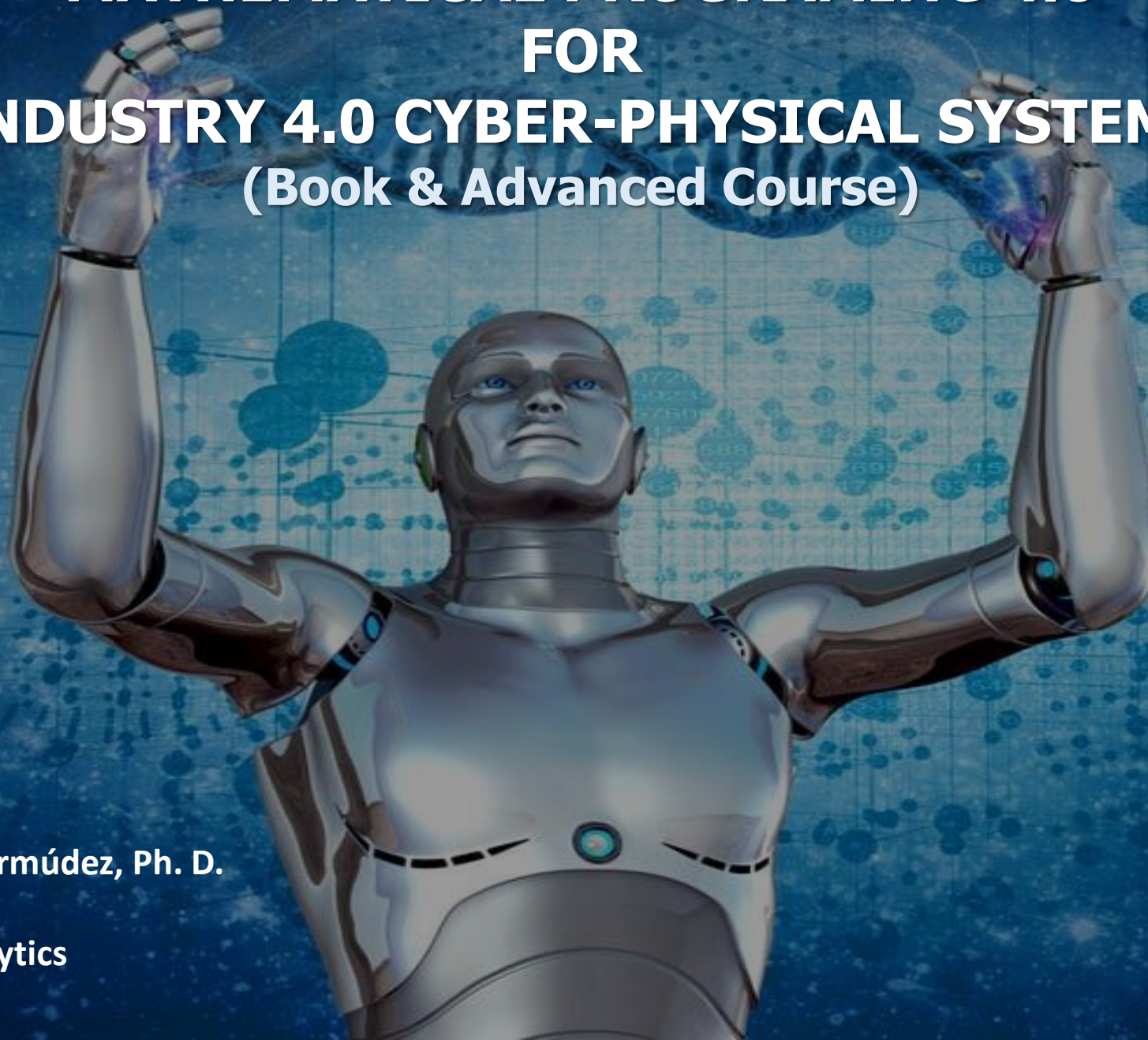




MATHEMATICAL PROGRAMING 4.0 FOR INDUSTRY 4.0 CYBER-PHYSICAL SYSTEMS (Book & Advanced Course)



Author
Eng. Jesus Velásquez-Bermúdez, Ph. D.
Chief Scientist
DecisionWare - DO Analytics
Bogotá, Colombia

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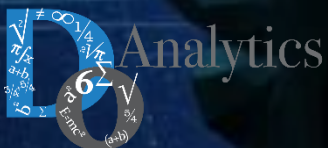
MATHEMATICAL PROGRAMING 4.0 & INDUSTRY 4.0

1. MATHEMATICAL PROGRAMING 4.0 FOR INDUSTRY 4.0 CYBER-PHYSICAL SYSTEMS
2. ENTERPRISE WIDE OPTIMIZATION & INDUSTRY 4.0
3. STRUCTURED MATH MODELING
MAKING & INTEGRATING MODELS AS A LEGO GAME
ROBOTIZING THE WRITING OF MATH MODELS
4. ROBOTIZING THE WRITING OF COMPLEX OPTIMIZATION MODELS
LARGE SCALE OPTIMIZATION METHODOLOGIES
AUTOMATIC CONVERSION OF DETERMINISTIC TO STOCHASTIC PROGRAMMING

March 5, 11, 19, 27

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**ITHAKA
(LIFE AS A JOURNEY)**

As you set out for Ithaka
hope the voyage is a long one,
full of adventure, full of discovery.
Laistrygonians and Cyclops,
angry Poseidon- don't be afraid of them:
you'll never find things like that on your way
as long as you keep your thoughts raised high,
as long as a rare excitement
stirs your spirit and your body.

Laistrygonians and Cyclops,
wild Poseidon- you won't encounter them
unless you bring them along inside your soul,
unless your soul sets them up in front of you.

May there be many a summer morning when,
with what pleasure, what joy,
you come into harbors seen for the first time;
may you stop at Phoenician trading stations
to buy fine things,
mother of pearl and coral, amber and ebony,
the sensual perfume of every kind-
as many sensual perfumes as you can;
and may you visit many Egyptian cities
to gather stores of knowledge from their scholars.

Keep Ithaka always in your mind.
Arriving there is what you are destined for.
But do not hurry the journey at all.
Better if it lasts for years,
so you are old by the time you reach the island,
wealthy with all you have gained on the way,
not expecting Ithaka to make you rich.
Ithaka gave you the marvelous journey.

Without her, you would not have set out.
She has nothing left to give you now.
And if you find her poor, Ithaka won't have fooled you.
Wise as you will have become, so full of experience,
you will have understood by then what these Ithakas mean.

Constantine P. Cavafy

Translated by Edmund Keeley/Phillip Sherrard

RESUME

The book is oriented to teach large-scale optimization courses, it presents the results of research and technological development carried out by the Eng. Jesús Maria Velásquez-Bermúdez, Ph. D., during 45 years of practice of the profession of Math Programmer, starting from the year 1974; user of the theories of large-scale optimization since 1978, primarily the theory of J. F. Benders. The collection of written material has been funded entirely by DecisionWare (**DW**), company with about twenty-five years (since 1995) in the market of the Mathematical Programming. The book collects experience and knowledge generated in real-life projects carried out since 1978.

All this knowledge is preserved at the level of the state-of-the-art of Mathematical Programming and Computer Science by the cognitive robots developed by **DW** (**OPTEX** and **SAAM**), as the way to keep updated models that have worked and evolved since 1991. At the present time (beginning in 2017) the software is being updated in accordance with the new concepts of cyber-physical spaces that support the new revolution **Industry 4.0** that connect the industrial growth with the assessment of the knowledge and with the ability to produce new knowledge from: i) past knowledge and ii) new information which generates continually big data, giving origin to the **knowledge-intensive industries**.

The book is aimed at professionals, researchers, teachers, advanced students who are interested in generating new knowledge through mathematics methodologies (algorithms) for the markets of Advanced Analytics solutions (predictive and prescriptive) and the generation of software according to: i) parallel computing (multi-CPU with multi-cores, multi-GPUs, multi-tensor processors and quantic computers), and ii) distributed optimization (multiple agents operating simultaneously in real time).

The book is in phase of editing and review. All the material is already written (95%), but it is in the phase of integration. The "final" version of the book will be available in March 2020.

Associated with the book, a course, virtual or face-to-face, has been designed to teach using the book as a guide text. The course is composed of as many sessions as chapters the book has, each session has two hours of conference.

For more information please send a mail to jesus.velasquez@decisionware.net

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MATHEMATICAL PROGRAMING 4.0 FOR INDUSTRY 4.0 CYBER-PHYSICAL SYSTEMS STRUCTURE

The Book has four parts

PART I – MATHEMATICAL PROGRAMMING & CYBER-PHYSICAL SYSTEMS

Whose aim is to present the Mathematical Foundations for the solution of the constrained optimization problems. It includes the economic interpretation of optimization models and the MPEC (Mathematical Programming with Equilibrium Constraints) problems. The different formats of the problems of optimization and algorithms to solve them are also presented briefly.

PART II – LARGE SCALE OPTIMIZATION METHODOLOGIES

Oriented to the presentation of the theoretical foundations of large-scale optimization, with emphasis on the atomization of the problems to solve them in parallel computers and/or in grid of computers. The goal is to present the integrated vision of the Real-Time Distributed Optimization (**RTDO**) as the mathematical way to modeling the cyber-physical systems of the Industry 4.0; that is characterized by integration of multiple algorithms which continuously cooperate to solve the problems of the multi-agent system, using independently the multiple computers of the agents and sharing information to achieve an optimal solution. This theory is built using the basic theories of partition and decomposition of problems (Benders, Lagrange, Dantzig-Wolfe,...).

PART III – A NEW PARADIGM: MAKING REAL-LIFE DSS USING ARTIFICIAL INTELLIGENCE

It presents a new view of the Mathematical Programming (Mathematical Programming 4.0) in order to:

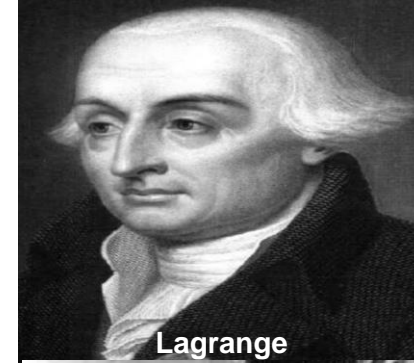
- i) Structure Mathematical Modeling Process in order to standardize the formulation of models mathematical models to make independent the algebraic formulation from de optimization technologies; this will facilitate the portability of mathematical models among multiple optimization technologies, which benefits users expanding the market of mathematical programming.
- ii) Robotization making use of the concepts of artificial intelligence to capitalize on expert systems the lessons learned as a form to facilitate the construction of the mega-models of the future.

The two points socialize the mathematical programming.

The concepts presented are based on the experience of the author (since 1991) in the development of solutions of problems through the development and use of the cognitive robot **OPTEX Optimization Expert System**.

PART IV & PART V– REAL-LIFE APPLICATIONS USING MATHEMATICAL PROGRAMMING 4.0

The chapters of this parts contain cases of real-fife application of the concepts presented based on engineering experiences of the author. Each chapter includes the algebraic formulation and the design of the computational implementation of the models; several of the chapters will include programming code in multiple optimization technologies: GAMS, C, AMPL, IBM OPL, MOSEI, PYTHON-PYOMO, , ...; These codes correspond to real cases and includes demo data.



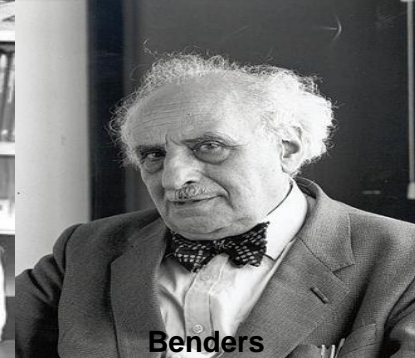
Lagrange



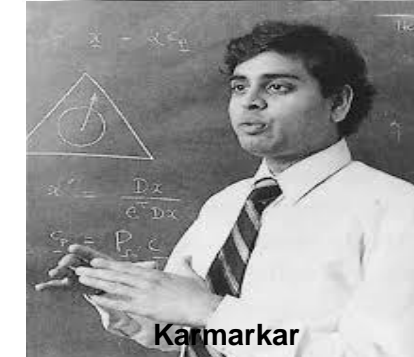
Dantzig



Bellman



Benders



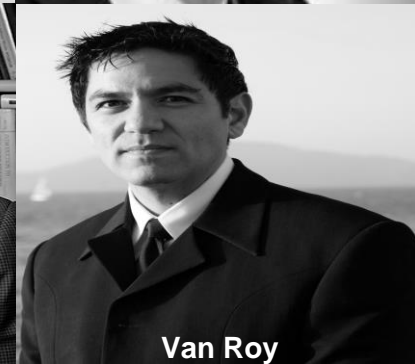
Karmarkar



Bixby



Grossmann



Van Roy

MATHEMATICAL PROGRAMING 4.0 FOR INDUSTRY 4.0 CYBER-PHYSICAL SYSTEMS

THEORY CHAPTERS & CLASSES

PART I – MATHEMATICAL PROGRAMMING & CYBER-PHYSICAL SYSTEMS

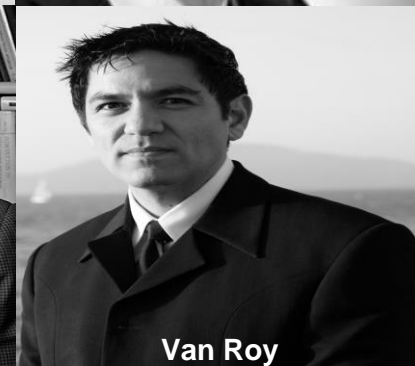
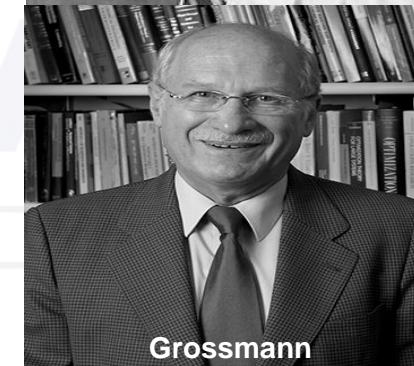
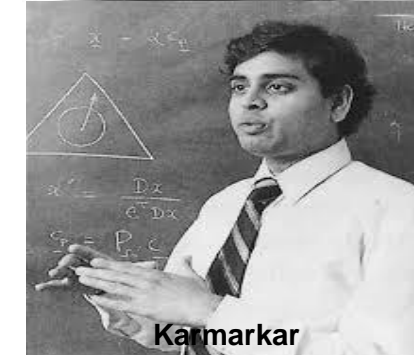
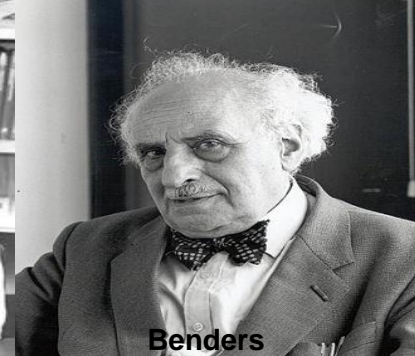
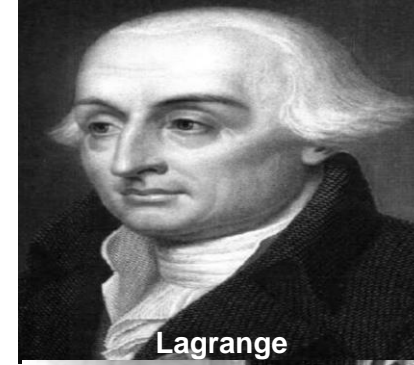
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 - Parallel Optimization as an Artificial Neural Network
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MATHEMATICAL PROGRAMING 4.0 FOR INDUSTRY 4.0 CYBER-PHYSICAL SYSTEMS

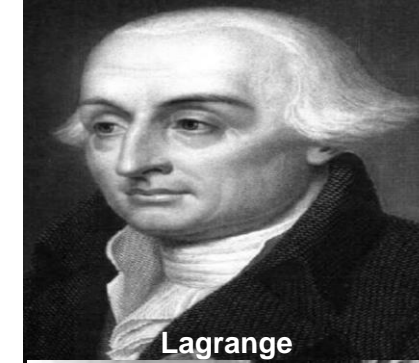
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9. Predictive Advanced Analytics I: Market Share Modeling using Syndicated Databases
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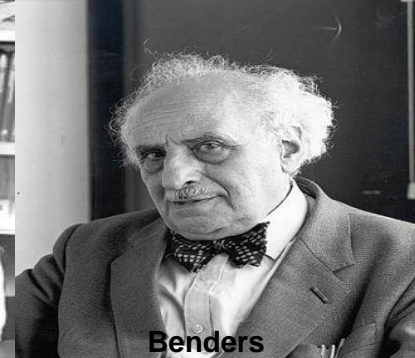
Lagrange



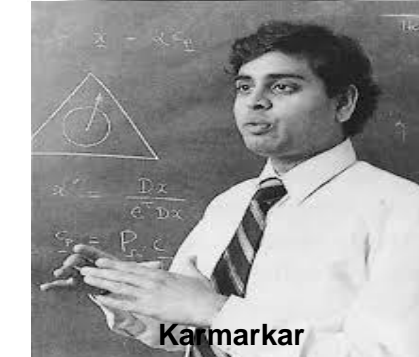
Dantzig



Bellman



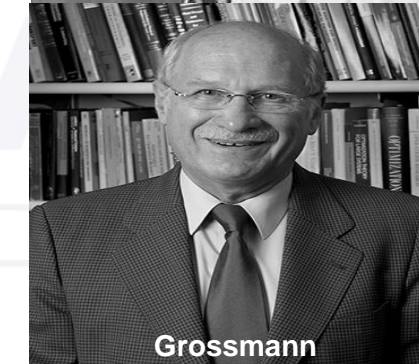
Benders



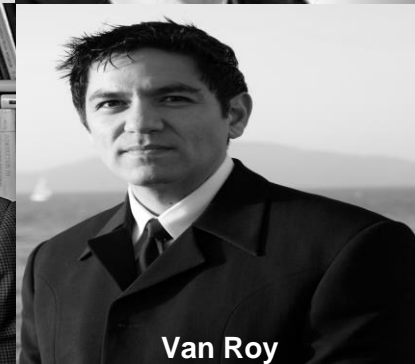
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Abstract.

This chapter is aimed to introduce the concepts of the vision of the author about the role of the Mathematical Programming as part of the Industrial Revolution 4.0. The book develops the mathematical and technological foundations that support this view.

The Mathematical Programming (MP), and in general the mathematical modeling based on algebraic equations, requires new ideas to meet the challenges of the future, which already is bringing fundamental changes in the way of doing things, this is reflected in the new industrial revolution, called Industry 4.0. The short-term requirements in Mathematical Programming are:

1. A new look of optimization according to the real-world technologies: i) Internet of Things (IoT), ii) Industrial Internet of Things (IIoT), iii) Smart Metering and Big Data, and iv) Robotization.
2. Standardization/normalization of mathematical programming modeling (structured mathematical modeling) that implies easy connection of multiple mathematical models so they can interact with each other. This requires a clear difference in academic training between mathematical models and optimization technologies.
3. Expert Optimization Systems that capitalized the knowledge about:
 - i) The formulation of the models (optimization technologies must be able to reuse previous formulations to generate new models) and
 - ii) The results of the optimization models (optimization technologies must be able to reuse the historic results to facilitate and to accelerate complex problem-solving processes).
4. Socialization of large-scale technologies to the community of mathematical modelers; these methodologies must be a basic knowledge not an expert knowledge; considering that they are necessities to make effective use of modern computing technologies (multi core CPUs, multiples GPUs, tensor processors and quantic computing) all based on parallel and distributed processing.
5. Development of algorithms that effectively solve basic problems, for the different formats of mathematical programming, using all computing technologies, so that a complex mathematical problem can be solved based on the atomization of a large-scale model in "hundreds/thousands" of small-scale problems.
6. Commercialization of large-scale methodologies that must be connected by parametrization, in a similar way that actually we connect the basic solvers. It must be the i) new generation of solvers and ii) high level algebraic languages.
7. The new environment must include the concept of Real Time Distributed Optimization (RTDO) in which multiple digital agents (robots) act simultaneously to cooperatively optimize, in real-time, a real-life problem based on agent-to-agent communication, which is the main feature of Industry 4.0.
8. Socialization of optimization in the organizations; this implied more end-users that understand that optimization is the analytical methodology that produces the greatest economic value (wealth) to organizations of all kinds: public or private, profit or nonprofit, large or small.
9. Development of cognitive robots (as is happening in all technological sectors) that facilitate the implementation of:
 - i) Complex algorithms that facilitate the implementation of Mathematical Programming 4.0;
 - ii) Automatic interfaces with the information systems that store data related to mathematical models, and
 - iii) Expert systems to support the design, developing, maintenance and use of complex mathematical models.

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 1. State-of-the-Art of Computer Technologies
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Abstract.

A summary of the basics that are required to work on optimization and meet the strong relationships between economics and mathematical programming:

Mathematical topics:

- Lagrange Theory
- Duality Theory
- Karush-Khun-Tucker (KKT) Conditions

Problem Formats:

- Linear Programmning
- Non-Linear Programmning
- Mixed Linear Programmning
- Quadratic Programming
- Mathematical Problems with Equilibrium Constraints
- Semidefinite Programming
- Surrogate Programming

Algorithms:

- Exterior Point Methods
- Interior Point Methods

DECISIONWARE

MAKING YOUR WORLD SMARTER

Abstract.

Economic topics:

- Lagrange Multipliers, Dual Variables, Marginal Costs
- Markets Modeling
- Equilibrium Modeling



DECISIONWARE
MAKING YOUR WORLD SMARTER

"Most of the things and processes that the humans use have been totally affected by technology, which has opened up to the human imagination producing previously unsuspected results; mathematical modeling should not escape this process; starting from discovering the mathematical foundations that serve to establish the laws governing physical, industrial, economic, social processes and with them to build mathematical models and increasingly powerful calculation algorithms; today all the knowledge and the technology is available to develop a new artificial intelligence that emulates the human hypothalamus in any type of human organization, it may be call the organization mathematical hypothalamus."

Abstract.

Partitioning and decomposition of large-scale models is a way to understand its functioning and to solve complex mathematical problems. There are many systems that can be partitioned and decomposed according as its structure:

1. Interconnected Electrical Systems: integrated by the hydraulic, electric and the gas sectors
2. Integrated Energy Systems: integrated by electric, oil, coal, gas, consumer and external sectors
3. Global Multi-Business Industrial Supply Chains: multi-echelon supply chains integrated by factories, distributions centers and market located in multiple regions/countries for many complementary products. An example is the oil supply chain integrated by exploration, production, transportation and refining sectors.

Another reason to break down systems is related to the functions of the decisions; an example is:

1. Strategic: related with the expansions of the supply chain, in the long term.
2. Tactical: related with the plan (goals) of the operations of the supply chain, in the medium term.
3. Operations: related with the actions and the technical specifications (specs) of each installation/area of the supply chain, in the short term.

In this case, models of different hierarchy must be interconnected to coordinate the correct evaluation of the projects and their subsequent execution. The links may be marginal costs (dual variables) and/or border conditions (primal variables). These systems are characterized by the set of families of problem that they include. For example, a model to optimize de investment in a multi-sectoral industrial system, ; the process followed is:

1. At the top level is the partition by the functionality of decisions: it corresponds to investments in expansion and simulation of operational decisions, which depend on multiple scenarios of the decision-making environment.
2. In the next step the system decomposition is done by random scenarios. This gives rise to a two-stage stochastic optimization model, known as L-Shape (Van Slyke and Wets, 1969)
3. Given that the system is multi-sector (for example, the energy sector: electricity, oil, gas and biofuels) it is possible to decompose the system in as many subproblems as couples <sectors-scenarios> exists. The Benders cuts may be decoupled, solving separate each subproblem.
4. To decrease the size of the subproblems, it is possible to make a new decomposition, in this case by zones.
5. Finally, a new decomposition can be based on the periods of the planning horizon.

Abstract.

Making a parallel with neural nets, the concept of problem family can be assimilated to a "neuron" class; and the optimization process can be defined as a complex communications system between "smart neurons". Basic neurons (perceptron) are based on perceptions that are added and processed in order to explain the behavior of the system based on adjustment of observations to history, but without ability to internally process the signals receiving.

If we define a type of problem such as a smart neuron which has autonomous capability, based on "universal" mathematical laws, to process the inputs from the environment (primal variables in the case of BT and dual variables in the case of LR) and produce the necessary information for another type of neuron processing, then we have a new type of neural net: a smart neural net, that is based in mathematical laws and not only in the perception of the historic data.

As was noted previously, different types of problems that make up a system based on multilevel partition and decomposition of physical systems. This means that the structure of the smart neural network corresponds one-to-one with the parts of the physical system and it is not the result of an empirical process in which many structures are tested as part of the analytical work oriented to determine the best structure that represents/perceives the system. For example, in a supply chain system all the relations between neurons are defined by the partition/decomposition protocols.

Abstract.

In 1962, J. F. Benders published his seminal theory in the paper "Partitioning Procedures for Solving Mixed Variables Programming Problems" oriented to optimization of mixed integer problems (MIP) that was been the origin of multiples methodologies oriented to solve large-scale problems related with stochastic complex combinatorial and/or dynamic systems. Since its formulation in 1962, the researchers in Benders Theory (BT) have proven that:

- i) BT is an effective methodology to solve complex problems that cannot be solved using only "best" basic optimization algorithms (CPLEX, GUROBI, XPRESS, ...);
- ii) Algorithms based in Benders' Theory can solve NP-hard (non-deterministic polynomial-time) problems in reasonable time; for this type of problems BT has proven to be an effective methodology to solve complex problems that cannot be solved using "best" mathematical solvers;
- iii) BT is a mature methodology that is in the accelerated growing phase, and iv) There is a gap between the research in mathematical programming and the application of the large-scale methodologies in real world solutions.

In this book, there are three chapters oriented to teach about Benders' Theory, enhancements and variations oriented to: i) Expand problems that can be solved based on Benders concepts, and ii) Speed-up the time of the solution of the complex problems. They are:

1. Chapter II-2: J. F. Benders: Theory, Variations and Enhancements. It contains the theoretical foundations of BT, major changes and improvements made to the theory of BT in order to:
 - i) Expand the ability of BT to solve problems in more complex formats that treaties originally by Benders that were limited to mixed integer (MIP) problems,
 - ii) Accelerate the solution process by modifying the original BT algorithm, and
 - iii) To decompose the original problem into multiple subproblems of smaller size in such a way that accelerate its solution time and prepare it for use parallel computing architectures.
2. Chapter II-4: Dynamics and Stochastic Benders Decomposition. Many BT applications focus on stochastic programming dynamic problems. This chapter presents the theoretical foundations of the BT applied to dynamic problems which are related to the of the principles of Dynamic Programming (DP) to address the problem. Two approaches are presented to solve the problem:
 - i) Nested Benders based on the decomposition (NBD) of the dynamic problem based on the future cost function of DP, and
 - ii) Generalized Dual Dynamic Programming (GDDP) which includes the differentiation of the variables of the problem in state variables and control variables; and it can be solved using the concepts of NBD or simply Benders decomposition.
3. Chapter II-5: G-SDDP – Implementation and Electric Sector Applications. It presents in detail the process of implementation of GDDP and G-SDDP and applications of the theory to various application cases in the electrical sector. It includes comparative analysis between the NBD and the GDDP and examples of the programs in GAMS.

The objective of this chapter is that reader learn about Benders Theory and its main variations and enhancements oriented to speed the solution of complex problems as a collection of coordinated sub-problems that make "easy" to solve the integrated problem.

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Abstract.

In the field of mathematical optimization, Stochastic Programming (SP) and Robust Optimization (RO) are frameworks for modeling optimization problems that involve uncertainty. This chapter considers four aspect about stochastic optimization, they are:

1. Stochastic Programing (SP) based on scenarios, also known as non-anticipative stochastic programming. SP considers multiple scenarios, associating each of them with a probability of occurrence, and the model determines the "best" decision before the occurrence of the scenario (non-anticipative decisions). This alternative requires a process to generate the scenarios, they may be exogenous (calculated outside of optimization model using a special stochastic model whose results are read as optimization parameters), or endogenous (calculated within the model optimization). It should be note, that in stochastic optimization there is not the "best" solution, in contrast to the deterministic optimization;
2. The risk management associated with decisions is a fundamental part of the analysis considering that optimize just the expected value of the objective function, may lead to decision highly risks (risk-prone) with greater risk (volatility) than other decisions that do not seek this goal. Two main aspects are considered: i) a risk measure and ii) the optimization problem used to make the risk management.
3. Basic concepts about the use of large-scale methodologies to solve complex SP problems due to the amount of scenarios involved in the analysis.
4. Robust Optimization (RO) is a field of optimization theory that deals with optimization problems in which a certain measure of robustness is sought against uncertainty that can be represented as deterministic variability in the value of the parameters of the problem itself and/or its solution

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Abstract.

This chapter presents a review of the use of the theories of partition and decomposition of Benders (BT), and its variations, emphasizing its use in complex dynamic stochastic systems. It includes theoretical considerations about the solution of dynamic optimization problems integrating the Benders Theory, the Dynamic Programming approach and the concepts of Discrete Control Theory.

Two methodologies are presented to solve the problem: Nested Benders Decomposition (NB) and Generalized Dual Dynamic Programming (GDDP), including their extensions to Stochastic Programming (SP).

The so called Generalized Dual Dynamic Programming Theory (GDDP) was initially published by Velasquez in 2002; it can be considered as an extension of previous approach known as Dual Dynamic Programming (DDP) a variation of Nested Benders (NB) methodologies. From the point of view of Dynamic Programming (DP), the main difference between the traditional Nested Benders (NB) methodologies and GDDP is that the conceptual formulation NB considers all the variables of the problem as state variables, while the GDDP makes a distinction between state variables and control variables. This distinction permits a more detailed algorithm in which the sub-problems are smaller than in the NB. The NB has been widely used in the economic dispatch of power systems. The main limitation of NB, including DDP, is that it only solves linear models.

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Abstract.

This chapter is oriented to study the computational implementation of the Generalized Dual Dynamic Programming (GDDP) and Generalized Stochastic Dual Dynamic Programming (G-SDDP). Implementation focuses on dynamic, and/or stochastic models; the concepts presented are typical of the GDDP/G-SDDP. The implementation only presents considerations for sequential computing, but they are critical to the implementation of parallel GDDP/G-SDDP algorithms, which is presented in a later chapter. The described process has been implemented in OPTEX Expert Optimization System (Velasquez 2018).

The first paper about GDDP/G-SDDP was published in 2002 (Velasquez 2002), it was not followed by the publication of the experimental results. This chapter includes several models with practical application in the electrical sector. The experiments show the speed-up of GDDP methodologies versus Nested Benders methodologies (NBD) and the robustness of GDDP/G-SDDP.

As conclusion, the conceptual formulation of the GDDP problem enables development of efficient algorithms based on the partition and the decomposition of the original problem using Benders' Theory and the conceptualization of Dynamic Programming. The concept presented can be extended to other large-scale methodologies that may be used in dynamic stochastic models, such as Lagrangean Relaxation.

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Abstract.

This chapter introduces two large-scale optimization methodologies: Lagrangean Relaxation and the Dantzig-Wolfe Decomposition principle which are strongly related to the basic concept: relaxation of restrictions of the original problem to break it into two problems: one master and another slave. The slave generates information to send problem can be decomposing to facilitate the solution of the entire problem. The slave problem generates information to be sent to the master problem and it may be decomposed in several subproblems to facilitate the resolution of the entire problem.

Fisher, 1981 presents the foundations of the generalization of the Theory of Lagrange and Karush-Kuhn-Tucker conditions (KKT, Hadley, 1972) that characterize the properties of an optimal point (maximum or minimum) of a restricted continuous optimization problem. To solve general mathematical optimization problems Lagrangean Relaxation (LR) relax the constraints of the original problem, or part of them, through successive estimates of Lagrange multipliers (dual variables) of the relaxed restrictions, to solve the original problem as a sequence of simpler problems.

Dantzig-Wolfe Decomposition (DWD) is an algorithm for solving linear programming problems with special structure. It was originally developed by George Dantzig and Philip Wolfe (1960). The equivalence between DWD and LR is well known (Lemarechal, 2003). Solving a linear program by Column Generation (CG), using DWD, is the same as solving the Lagrangean Dual by Kelley's cutting plane method (Kelley, 1960).

At the end the application of the concepts studied to the problem of planning and scheduling operations in a maritime petroleum field on the continental shelf west of Norway is presented.

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3.6.	RESULTS

Abstract.

Cross Decomposition (CD) is an approach to solve large-scale stochastic dynamic optimization problems using the combination of Large-Scale Optimization Methodologies developed by Benjamin Van Roy (1983); CD presents the principles for integrating Benders Partition and Decomposition Theory (Benders 1962, BT) with Lagrangean Relaxation (Fisher 1981, LR) and/or with Dantzig-Wolfe Decomposition (DWD). CD is applied when the coordinator-sub-problem partition has been performed and the math modeler wants to perform a new partition or decomposition on the coordinator, and/or in the subproblem, using a different, or the same basic theory, than the one previously used.

CD may be defined as the harmonious coordination of communications between the different type of sub-problems, where in each of them the information is processed according to the basic theory used, BT or LR or DWD, and information is exchanged according to the connectivity of the hierarchical scheme of sub-problems. The type of subproblems are associated with problems families that are related to zones, sectors, time, class of decision (investment or operations) and/or stochastic conditions.

However, while there are many papers that focus on improvements for one of the main decomposition schemes (BT, LR and DWD), it seems that only few research efforts address combining their complementary strengths. For example, in November 2019, using Google Scholar searches the publications results are: i) "cross-decomposition": 1220, ii) "Benders Decomposition" + "Lagrangean Decomposition" + "Cross Decomposition", iii) "Benders Decomposition" + "Lagrangean Decomposition" + "Cross Decomposition" + "Stochastic Programming": 40; as reference the total publications on "Benders Decomposition" was 20.700. This implies that Cross Decomposition and its variations is an open research topic in Mathematical Programming.

The chapter is divided into three parts:

1. The basic theory of CD is presented to introduce the reader to the subject
2. A summary of an application by Mitra et. al (2014) is presented to show the benefits of CD in terms of accelerating the solution process of complex problems.
3. A theoretical large-scale case is analyzed, with the idea of showing the reader the power of CD to atomize complex problems to take advantage of the dynamic structures and parallel computing.

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Abstract.

In edition



DECISIONWARE
MAKING YOUR WORLD SMARTER

Abstract.

In edition



DECISIONWARE
MAKING YOUR WORLD SMARTER

Abstract.

This chapter presents the "**Surrogate Mathematical Programming**" (**SMP**) developed by Greenberg & Pierskalla's (1970) and the design and implementation of the **PDS, Primal Dual Surrogate Algorithm** for nonlinear convex programming developed by Velásquez (1986).

The first work in this area was showed by Glover (1965) who uses surrogate constraints to solve binary optimization problems. Afterwards, works of Balas (1969), Geoffrion (1967) and again Glover (1968) are found. They present the uses of surrogate constraints to the same problem. Greenberg & Pierskalla developed the bases of a general theory for Surrogate Programming which may be classified as a Lagrangean Method. One of the firsts works in this area is the model called Generalized Lagrange Multiplier (GLM) developed by Everett (1963).

SMP solved a general nonlinear problem by a sequence of unconstrained problems using the Lagrange multipliers. One of the difficulties to use this methodology is the existence of gaps for multipliers that solve the original problem. Greenberg & Pierskalla (1970) show that the gap problem in the case of Surrogate Programming is less restrictive than the surrogate GLM model. They suggest that the solution of a nonlinear problem may be obtained by a problem with only one surrogate constraint.

The first section presents the fundamental theory which supports the Surrogate Programming. The second section introduces the P.D.S. Primal-Dual Surrogate Algorithm. The third section presents the application of PDS to solve (mixed) non-linear problem related to Economic Load Dispatch Including Transmission Losses using GAMS. The first document about the PDS algorithm was wrote and presented by Velásquez in 1986; this document is based in that publication.

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3. ECONOMIC LOAD DISPATCH INCLUDING TRANSMISSION LOSSES
 - 3.1. Problem Formulation
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4. SPECIAL CASES
 - 4.1. Linear Programming
 - 4.2. Quadratic Programming

Abstract.

In edition



DECISIONWARE
MAKING YOUR WORLD SMARTER

Abstract.

In the prologue of the book "Parallel Optimization: Theory, Algorithms and Applications", wrote by Censor and Zenios (1997), the Professor Dantzig said: "the fascinating new world of parallel optimization using parallel processors, computers capable of doing an enormous number of complex operations in a nanosecond", additionally he said "according to an old adage, the whole can sometimes be much more than the sum of its parts, I am thoroughly in agreement with the authors, belief in the added value of bringing together applications, mathematical algorithms and parallel computing techniques". This is exactly what the mathematical modeler found true in Parallel Optimization.

Despite the time elapsed since the first applications of parallel optimization, in 1991, this methodology is only beginning to develop since is recent the time in which multi-processing is massive and become the low-cost multi-core computers. Therefore, it is expected that in the coming years the research on parallel optimization and speed of solving complex problems increases significantly.

Mathematical methodologies to solve large-scale optimization problems based in the atomization (mixing decomposition and partition) of the mathematical models to solve them using the power of state-of-the art of parallel computing (CPUs, GPUs, Tensor Processors and Quantum computers).

Asynchronous Parallel Optimization (APO, Velasquez, 1995, 1997) in this book is defined as act of solve an optimization problem using multiple cores in a computer, or in a grid of computers, using the moderns multiprocessing environments; joining the decomposition and the partition large-scale theories (Benders Theory, Lagrangean Relaxation and Dantzig-Wolfe Decomposition) that permits structure complex multilevel mathematical models; these systems are characterized by the set of problem families that they include.

It is convenient to define two terms:

1. Partition: the action of dividing a problem into two subproblems establishing a hierarchical relationship between them.
2. Decomposition: the action of dividing a problem in to multiple subproblems with the same level in a hierarchical scale.

These definitions are valid in this book, but the reader is caution that they are not universal definitions

The mathematical modeler should be aware that to develop this type of application requires knowledge about the formalities which must be considered to implement applications of parallel computing of any kind; for example, the fundamentals of the implementation of a DCS (Distributed Control Systems) or of a SCADA (Supervisory Control And Data Acquisition) may help, these computer industrial systems implies the permanent communication between many task that altogether assume the integrated management and control of the industrial system in a multi-tasking environment.

Abstract.

Real-Time Distributed Optimization is the distribution of the optimization process in many agents that act simultaneous and independently when they received information from the its exogenous environment. The process can be summarized in the following steps:

1. From a top-down analysis mathematical is possible to construct mathematical or logical rules of interaction between multiple agents (representing each part of the system), which can represent the "state of the reality",
2. Starting from the math/logic rules, following an approach bottom-up, is possible to build segmented/atomized models of the real-world.

Using asynchronous optimization processing, it is possible to define the actions of an agent that keep the system on the "optimality path" in a cyber-physical system.

1. Real-Time Distributed Optimization
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3. Distributed Optimization as An Artificial Smart Neural Net
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 - 4.1. Industrial Supply Chain
 - 4.2. Routing
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 - 4.4. Flexible Distribution & Transmission Systems
 - 4.5. Smart Grids

Abstract.

Structured Mathematical Modeling (SMM) is defined, by the author, as a fundamental step in the process of socialization of the mathematical modeling, it is a necessity to ensure that the benefits arising from the applied mathematics extend to the as many people as possible. This cannot be achieved, while the mathematical modeling is not within the reach of most professionals in engineering, economics and management sciences.

The main barriers must be overcome is the dependence of mathematical models from the Mathematical Programming technologies used to implement the models. The alternative is to normalize the formulation in such a way to ensure their portability between technological platforms. This standardization would allow professionals interested in the mathematical modeling the possibility of formulating their own models without to know in depth the syntax of a computer language; this fact would expand the number of mathematical modelers and diminish the level of expert knowledge required to formulate mathematical models. The standardization process must define:

1. SMM Basic: the part of the mathematical modeling process that is included in the standard. This implies: i) regulate by a common agreement made by the representatives of all the mathematical modeling-related communities, and ii) that it should be "mandatory" for the industry and
2. SMM Advanced: the part of the process that is covered by the optimization companies, as a way of differentiation of products and services offered; it is not binding, but it is convenient for humanity.

In case that the mathematical modeling world community does not get in accordance with a global SMM, as it is suggested here, the ideas of this document can provide guidance for the organizations that management/produce large number of mathematical models, they can make an internal standard, which allows to capitalize the value added by the normalization.

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2. Mathematical Programming: A Natural Standard
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4. Integration of Multiple Models and Problems
5. IoT, IIoT and Dynamic of Smart Metering
6. Problem Solution
7. Large Scale Optimization Methodologies
8. Stochastic Optimization

Abstract.

The actual mathematical models that can be solved today can be large in size. In general, the math modelers should be aware of: i) the number of algebraic variables and constraints can be in the order of hundreds, ii) when the restrictions are expanded, the numerical model can handle millions of variables and constraints. Then the math modelers must be prepared to handle this problem making use of the methodologies and technologies of information systems, since manual methods cannot guarantee the quality of the data management. For this reason, it needs to be included within the technologies that are required for the implementation of real-world Decision Support Systems (DSS) include information systems, which complements mathematical programming knowledge.

Edgar Frank Codd was an English computer scientist invented the relational model for database management, the theoretical basis for relational databases and relational database management systems, his most mentioned, analyzed and celebrated achievement. Codd's theorem states that relational algebra and the domain-independent relational calculus queries, two well-known foundational query languages for the relational model, are precisely equivalent in expressive power. That is, a database query can be formulated in one language if and only if it can be expressed in the other.

Codd's Theorem is notable since it establishes the equivalence of two syntactically quite dissimilar languages: relational algebra is a variable-free language, while relational calculus is a logical language with variables and quantification.

For traditional modelers, tackling this process involves changing focus to handle the algebraic formulation of mathematical models, which must migrate from an academic formulation based on Greek letters (less than 30 options) to a formulation based on primary key coding system.

With the above in mind, it is proposed that the Structured Mathematical Modeling will be supported in the storage of all its components in RDBs.

These concepts are implemented in OPTEx Optimization Expert System; a cognitive robot that facilitates the implementation of complex mathematical models according to the requirements of modern times.

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Abstract.

Structured Mathematical Modeling (SMM) standardizes the management of entities and relationships centered about its database algebraic language that must allow management of linear and non-linear equations.

Sort the elements that are part of a mathematical model around the concepts of RDB involves the need to structure the process of mathematical modeling in a way to store all elements in the tables of the SMM; this implies organize the mathematical model from an "universal" point of view of a relational information system; then, it is possible to affirm that the information system that supports SMM mathematical modeling is the first step towards normalization of the algebraic formulation and the use of mathematical models.

The implementation of the SMM can be arranged by stages (levels), at least two must be considered:

1. SMM Basic: includes entities related with:
 - i) Integrated basic models and
 - ii) Industrial Data Information System (IDIS) Data Model.
2. SMM Advanced: includes entities related with multi-problem models, large-scale technologies, parallel optimization, real-time distributed optimization and decision support systems.

The entities that are part of the SMM can be divided into three groups:

1. Formulation of Mathematical Models, entities used in the formulation of mathematical models, it must be included in SMM Basic.
2. Advanced Mathematical Modeling, entities used in the formulation of multi-problem mathematical models, it must be included in SMM Advanced.
3. Industrial Data Information System (IDIS) Data Model, entities used in the formulation of data model of IDIS, it must be included in SMM Basic.

The chapter presents in detail the implementation of a mathematical model following the guidelines defined in the previous two chapters. The chapter support material includes computer programs used for the implementation of real-life models, developed according to the defined guidelines.

INDEX

1. Basic Components
2. Formulation of Mathematical Models
3. Advanced Mathematical Modeling
4. Industrial Data Information System (IDIS) Data Model

Abstract.

In artificial intelligence, an Expert System (ES) is a knowledge-based computer system that emulates the decision-making ability of a human expert, providing power and helping to the decision-maker ability of using a knowledge-based architecture where the knowledge represents facts about the world that help the humans to make better decisions.

Expert systems are designed to solve complex problems by reasoning through bodies of knowledge, represented mainly as if-then rules rather than through conventional procedural code.

The inference engine is an automated reasoning system that evaluates the current state of the knowledge-base, applies relevant rules, and then asserts new knowledge into the knowledge base. The inference engine may also include abilities for explanation, so that it can explain to a user the chain of reasoning used to arrive at a conclusion by tracing back over the chain of rules that resulted in the assertion.

Just as in many areas of applied knowledge, if all accumulated knowledge generated developing and running mathematical models is stored in an information system then develop a new mathematical model is not a new story, it is the continuation of a current story, going on.

Two types of knowledge can be stored in the Optimization Expert System database:

1. Mathematical components (equations, problems, models, ...) previously used and working properly
2. Results of previous runs to speed up/facilitate the resolution of new problems.

As a database of a scientific process, if well built, it ensures that all stored knowledge works 100% well; the new information to be stored are improvements to the scientific process (mathematical models) and results of new experiments.

An important aspect of modeling of complex systems is the presumption that optimization should be done in a single pass, in which the optimization model starts from zero and reaches the optimum in one step; in a lot of cases, the time available is insufficient to solve the complex problem with the required precision. This was valid when processing capacity and RAM and disk capacities were a scarce resource, it is not true today. Today it is possible to have idle computer processing capability, or can be rented at a low cost, this implies the change of the concept of starting from scratch, to pre-preprocessing before during the time the mathematical model is not required.

The basic idea is that scheduling, routing or real-time optimization applications never optimize from scratch, perhaps the first time, but once launched an optimization application can be conceived as a permanent process of re-optimization which can occur at any time. This fact implies the need to create an RDB to store the optimization results for use in the future we called this function as Optimization Expert System (OES).

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Smart Algorithms that Make Advanced Analytical Algorithms

Abstract.

A robot is an artificial agent, meaning it acts instead of a person, doing things. Robots are usually machines controlled by a computer program or by electronic circuitry. The robot can be a physical mechanical mechanism and/or a virtual software system.

The Cognitive Robot (CR) is fundamental for Industry 4.0, it is based on concepts of AI, that writes advanced analytics algorithms that are required for the digital transformation of enterprises, CR automatically linking them to the enterprise information system; in summary, CR is a skilled robot that creates robots for complex processes using advanced mathematical methodologies (state-of-the-art). This robotization process is at the highest level of automation, because it does not replace manual human work but supports the construction of robots replacing human cognitive tasks, related to the optimization modeling of stochastic processes and/or business/industrial processes.

CR increases productivity of mathematical modeler; understanding productivity such as: make more models in less time and ensuring the quality of the produced algorithms.

To develop CR is necessary the Structured Mathematical Modeling (SMM), this makes CR independent of industrial mathematical technologies. As well as in the manual work robots enhance human ability, in the cognitive process, robots promote knowledge, systematized the cognitive tasks that are repetitive, like: i) write programs (in at least one optimization technology), ii) check data of IDIS, iii) data analytics, iv) check the mathematical formulation store in MMIS, ... , all these free of errors. Then CR speed-up the development times; changes in a model that works properly are implemented in minutes/hours.

Abstract.

OPTEX Optimization Expert System is a robot, based on concepts of Artificial Intelligence, that writes advanced analytics algorithms that are required for the digital transformation of enterprises. OPTEX automatically linking them to the enterprise information system; in summary, OPTEX is a skilled robot that creates robots for complex processes using advanced mathematical methodologies (state-of-the-art). This robotization process is at the highest level of automation, because it does not replace manual human work but supports the construction of robots replacing human cognitive tasks, related to the modeling of stochastic processes or business/industrial processes optimization. OPTEX is result of praxis, since it has been used in several industrial/commercial projects that give rise to practices included in OPTEX.

OPTEX increases productivity of mathematical modeler; understanding productivity such as: make more models in less time, ensuring the quality of the produced algorithms. For this purpose, the process of mathematical modeling has been normalized and standardized, this makes OPTEX independent of industrial mathematical technologies. As well as in the manual work robots enhance human ability, in the cognitive process, robots promote knowledge, systematized all tasks that are repetitive.

The cognitive robots are fundamentals for Industry 4.0.

The reader can download the Installation Manual and send e-mail requiring a License for a Beta Version of **OPTEX - Optimization Expert System**:
<https://www.linkedin.com/pulse/optex-optimization-expert-system-new-approach-make-models-velasquez/>

Abstract.

Stochastic Advanced Analytics Modeling (SAAM) is the name give (for the author) to a general approach to support **Machine Learning (ML)**, or Predictive Advanced Analytics, solutions developed using Mathematical Programming concepts including large scale optimization technologies.

There are many applications that can be implemented using the mathematical models included in **SAAM**; in general terms, these applications make up what is known as Data Mining (DM), today better known as Advanced Analytics:

- Discriminant Analysis
- Support Vector Machines (**GSVM**) and Support Vector Regression (**GSVR**), and Support Vector Data Description (**SVDD**)
- Artificial Neural Nets (**ANN**): Deep Neural Networks (**DNN**)
- Markovian Process: Markovian Nets and Markovian Decision Process (**MDP**)
- Clustering Analysis (**CA**)
- Advanced Probabilistic Models (**APM**): S-ARIMAX-GARCH Models
- Discriminant Analysis (**DA**) and Logistic Regression (**LR**)
- Bayesian Methods (**BM**)
- State Estimation (**SE**): Kalman Filter, Standard Kalman Filter (**KF**), Multi-State Kalman Filter (**MS-KF**) and Dual Kalman Filter (**D-KF**)
- Bayesian Ensemble of Models (**BEM**)
- Data Envelopment Analysis (**DEA**)
- Conjoint Analysis

The advantage of having all predictive methodologies under the mathematical programming format lies in the fact that it is possible to integrate easily basic predictive analytics methodologies with prescriptive optimization models. A case applied to a Revenue Management application is presented for a transport broker under the modality **LTL** (Less-Than-Truckload) Transport Networks.

In practice, **SAAM** is cognitive robot that has been developed to support Predictive Advanced Analytics solutions. More information about **SAAM** in: <https://www.linkedin.com/pulse/stochastic-advanced-analytics-modeling-opchain-saam-jesus-velasquez/>

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Abstract.

At the end of the last century SCM was a relatively new term that brought together the concepts of integrated business planning that have been used for many years by logistics experts, strategists and experts in Operations Research. Today, integrated planning based on mathematical models of optimization is the standard possible due to advances in information technology (high and low-level parallel computing, optimization algorithms, data transmission capabilities, platforms for the development of mathematical models).

There are four dimensions of the optimal synchronization of a supply chain, namely:

- Functional associated with the purchase, manufacture, transport and storage of industrial supplies and products
- Space associated with activities through industrial facilities and the different forms of markets.
- Internal associated with the hierarchy of decisions: strategic, tactical and operational.
- Business that responds to the purposes of strategic and tactical planning within the organization. Business integration makes SCM one of the components of a broader vision of integrated planning.

This improves the competitive advantage, reduce costs and increase profits, then managers seek to integrate planning activities of its value chain, which, originally, was understood as the sum of the Supply Chain Management (SCM) and Demand Chain Management (DCM). Today, this concept has expanded and covers all the functional areas of the organization including financial and human resources chains.

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Abstract.



DECISIONWARE

MAKING YOUR WORLD SMARTER

READY TO REVIEWERS

Abstract.

This chapter present the full implementation of **S&OP/BEER** a Decision Support System (**DSS**) to support the Sales and Operating Planning (**S&OP**) Process in **BEER-EXPRESS** (a hypothetic enterprise in the beer sector).

S&OP/BEER supports the process of optimizing the aggregate planning of industrial and logistics operations consisting of defining quantitative goals, among other, for:

- Weekly/monthly volumes produced in the production lines.
- Assign final products to be distributed among facilities
- Selection of modes of transport to be used

S&OP/BEER produces quantitative goals, among other, for:

- **Production Quantities:** For each process line and determines the optimal level of production for each product.
- **Packaged quantities:** for each line of packaging and for each product end determines the optimum amount of packaging.
- **Inventory levels:** for each storage produces the optimum level of inventory at the end of each period. It is considered the freshness character of beer.
- **Resources Consumption:** for all the resources involved in the productive process determines its level of consumption in each plant, packing line, ...
- **Optimum Blending:** for products from flexible production formulas, the model determines the optimal blending.
- **Labor Allocation:** determines whether it is necessary to hire extra shifts, in accordance with trade union rules, or if supernumeraries are required, to achieve production goals.
- **Product Transfers:** volumes of transfers of raw material, parts, end products between facilities that are part of the supply chain.

The end user can select the objective function to use according to his criteria, the most used are:

- **Minimize production costs**, assuming a demand which must meet, or
- **Revenue maximization** by selecting products that are more profitable to produce, according to the structure of the supply chain.

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Abstract.

The integration of the financial models (Assets Liabilities Management, **ALM**) with strategic/tactical supply chain models: i) Supply Chain Design (SCD) and ii) Sales & Operations Planning (**S&OP**) implies a holistic vision of the global enterprises.

The Financial Supply Chain Management (**FSCM**) must be oriented to optimize financial processes, helping companies to look, from a holistic point of view, the financial situation as result of: i) the final products Supply Chain Management (SCM) and, if possible, ii) the demand chain management (sales and marketing). This holistic approach focuses on the collaboration of all functions within the economic value chain of the organization. Corporate financial management consists on numerical calculations and therefore it is an excellent candidate for planning based on prescriptive mathematical optimization models; however, still not been widespread recognition of the importance of integrating to decision-making process based on optimization.

The connection of the financial models (**ALM**) with operations models (**SCM**, Supply Chain Management, and **SCD**, Supply Chain Design) provides, as a minimum gain, automatic generation of financial statements: i) losses and gains, ii) cash flow and iii) balance of assets and liabilities, what is usually done based on an independent post-processing that consumes time and effort of planners. As a substantial improvement to the decision-making process, the linkage of financial model with models of "supply chain" allows to optimize:

- Cash flow and treasury management
- Working capital
- Fiscal management (dividends, capital repatriation, payment/prepayment of liabilities, ...)
- Capital and equity structure
- Transfer pricing
- Corporate financial risk analysis.

This chapter presents the case of Industrial Operations and Financial Integrated Planning applied to a realistic case in a beer industry.

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Abstract.

This chapter presents the conceptualization of models oriented to the planning of bio-industrial supply chains. They are called bio-industrials because it covers: (i) the agricultural sector, the agricultural sector and the fishery sector.

Traditionally, bio-industrial supply chains have been considered to be composed of two major links: i) primary, related to the production of earthy animals, and/or fish, and/or vegetables, and ii) industrial, related to the processing of biological raw material to produce higher value-added food.

The advent of the energy revolution (that targets clean and renewable energy sources, one of them: the biome made up of animal excreta and plant crop residues) have led to a restructuring of the agro-industrial chains that can be considered composed of a new link and a new market: energy. In addition, some sectors, such as forestry, should be considered to provide environmental services necessary to maintain the balance of the planet.

This implies that at every level of planning, the resource competition between food and energy sectors must be considered. They are once complementary, but in other cases they are frontal competence.

All cases are based on real-life applications.

Given the importance of food to humanity, bio-industrial planning must be viewed from at least two points of view: the state and the private entrepreneurs. Rulers must ensure the correct use of soils in order to maximize their productivity and avoid the risks of natural (fire, floods, ...) and human (terrorism) disasters that can affect the economic sustainability of the agro-industrial sector and thus the food safety of the. Entrepreneurs must ensure the profitability of their companies.

Due to the extensive problem, three topics have been selected to study:

1. Agricultural land use planning for agricultural land use
2. Planning food supply to large cities/regions
3. Optimizing agro-industrial supply chains

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Abstract.

RESILIENCE

It is the ability to withstand and recover from severe shocks ("disasters") to continue the "normal" operation and ensure the fulfillment of its functions.

The industry, mainly the high-tech industry, during 2010, 2011 and 2012 was severely affected by a wave of natural disasters.

Disruptive disasters are not only limited to global supply chains, they also extend to national and/or regional chains that are increasingly affected by natural disasters, many of them arising from climate change and social events, such as social protests that disrupt the free flow of people and products. They can also be considered as disruptive events such as unexpected changes in material prices, whether raw materials or terminal products.

In view of these risks, the criteria for the design of logistics networks have had to be adjusted to include the methodologies necessary to protect companies from disruptive events by limiting their financial impact and increasing their resilience.

More information in

- Chapter IV-6
Resilient Logistics Networks Design.
Case: Design of Resilient Networks Using Stochastic Programming.
(Spanish Version)

<http://www.doanalytics.net/Documents/Chapter-IV-6-Resilient-Logistics-Networks-Design-Spanish-Version.pdf>

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Abstract.

There are two alternatives for modeling operation scheduling: discrete time models and continuous time models.

The chapter presents a generic overview of continuous time modeling for operational models that require coordinating in detail the start and end of all activities that are part of an operations plan. The conceptualization of modeling is generic, in the sense that it can be applied to any operations programming in a supply chain.

A real case of applying this modeling approach is presented for a pharmaceutical industry

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Abstract.

Multi-Echelon Dynamic Inventory & Stochastic Optimization (MEIO) corresponds to a mathematical model aimed at supporting the analytical process of defining inventory management policies to determine minimum levels of material inventory (products finals, parts, spare parts, raw materials), by optimizing the sourcing policy considering the generation of random scenarios (Monte Carlo simulation).

MEIO aims to determine the parameters of a dynamic inventory policy obtained from a multi-product production/distribution environment; MEIO considers in detail all the costs associated with purchasing, transporting and managing inventories.

MEIO uses the concepts of so-called non-anticipative stochastic programming which is based on the simultaneous analysis of multiple random scenarios with the aim of making decisions common to all of them that optimize the expected value of (cost minimization or expected profits maximization) while setting limits on assumed risk.

The math modeling includes:

- Procurement process (global sourcing)
- Dynamic demand of raw materials and inputs
- Exogenous dynamic demand of end products
- Customer service level
- Distribution network
- Inventory Types (normal, perishable, maturable, ...)
- Shared Resources
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Abstract.

Economic and operability benefits associated with better industrial blend scheduling are numerous and significant, because its application is widespread in the industrial environment.

The most elementary problem of mixing materials is the known problem of the diet of food to feed living beings.

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Abstract.

The objective of this chapter is the presentation of an example of detailed modeling in the process industry and in the minerals industry, for this purpose a model developed for a cement company is used. The modeling of the physical-chemical processes that occur along the cement chain is analyzed in detail in order to allow the reader to use it in his own company and in similar processes.

Topical follow-ups are studied in detail.

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- Fuel mix
- Modeling of fine cement grinding.

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Abstract.

The planning and scheduling of transport operations of products through pipelines: oil and refined products pipelines, aqueducts and mineral pipelines is done using three coordinated models:

- **Sales & Operations Planning (S&OP)**: determines the total optimal volumes transferred during the planning periods, without regard to the sequence of products in the pipeline.
- **Scheduling Operations (SCH)**: determines the volumes and the sequence of batches/tenders to transfer during the planning period, whereas the volumetric planning established in the previous model;
- **Real-Time Optimization (RT)** determines transfer speeds, pressures discharge and pumping stations operation patterns to meet the programming of batches/tenders.

The equations in the three models are virtually the same, the difference is in the way how the energy losses are calculated, and the sequence of the pumps are handled. In this case an integral DSS can be implemented according to the principles of the **Mathematical Programing 4.0**.

Crude pipelines transport oil from fields to refineries or to the exporting or from importing ports to the refineries. Flow in the pipes is multi-phase (mixed liquids of different density and gas), implying different hydraulic conditions between the oil pipelines and the refined pipeline and gas pipelines.

In this case RT focuses on the optimization of the operation of the pipeline once established the scheduling of batches/tenders of different types of crude oil (or refined products) that determines the volume that must be transferred. The RT programming (on the order of minutes) focuses on determining the use pumping systems plan that includes: i) pumps and patterns of operation, series or parallel connectivity, and ii) operational characteristics, transfer flow and discharge pressure). The amount of energy consumed has a non-linear behavior (polynomial) regarding operational characteristics. Alternatives to set up the pumping system (operation patterns) involving discontinuities in the consumption of energy resources that are required at the time of enabling or disabling a bomb.

Normally the objective of optimization is to minimize operating costs throughout the process of planning and scheduling (economic criteria), but this goal can come into competition with the minimization of the energy consumption (environmental criteria) when the energy cost change over time due to the electric power rates or to marginal costs of the electric system, This variations may occur during: i) the day, ii) of different days of the week and iii) the months of the year. This makes the problem of RT in a MINLP problem very difficult to solve in real cases. The approach has two steps: i) represent the pumping stations by non-convex hulls (computed offline), and ii) break down the system at two levels: a temporary coordinator for movements of batches along the pipeline that coordinates the temporal operation of pumps for each period of the planning horizon.

More information: <https://www.linkedin.com/pulse/oil-pipelines-real-time-optimization-jesus-velasquez/>

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Abstract.

More information in

- **Industrial Assets Maintenance Optimization**

<https://www.linkedin.com/pulse/industrial-assets-maintenance-optimization-plant-jesus-velasquez/>



DECISIONWARE
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Abstract.

The implementation of a Decision Support System, DSS, associated with the land use planning for a city, and its adjoin region, involve the implementation of a set of mathematical models representing the logic of the urban-rural macro/micro-economic process that represents the way in which people and companies are located in the space, according to their own interests, respecting the rules of the land use determined by the regional government, who should plan the long-term investments needed to meet the offer of social services that must support the region, as a global and autonomous entity. This is difficult, perhaps impossible, to get in only one mathematical model, and therefore is required to develop several models that generate the information needed to support the decision-makers in the process of taking the "best" decisions for the inhabitants of the region. This chapter describes the work realized to implement this DSS for Medellin City.

More information in **Integrated Regional Planning. Cities & Regions: Smart, Analytical & Sustainable**

<https://www.linkedin.com/pulse/integrated-regional-planning-cities-regions-smart-jesus-velasquez/>

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Abstract.

Smart metering systems directly impact the use of optimization in real-life problems. The conventional is to think that a problem is solved at a given moment and turns to meet periodically every hour, every day,...; this presupposes that the information that is required to run the model is achieved from a run to the next, but the big-data generated by the smart-metering systems change completely the decision-making environment.

To view the impact, consider a problem easy to formulate as the VRP-TW (Vehicle Routing Problem with Time-Windows). Traditionally, a routing urban model runs n times in a day, and it assumes constant the expected travel times between each pair of nodes in the network; however, it is aware that in cities with congested traffic networks, this hypothesis does not correspond to reality. But trying to change this hypothesis involved complications since there were no organized measurement systems that could generate the information required to consider the travel times as a function of the time of departure of the vehicle from a specific node and linking such times to a specific path (sequence of streets) between two points on the network. The routing solution would be changed by the occurrence of exogenous events or when occurs the time limit for new routing; but keeps the hypothesis of time-independent travel times.

However, the situation today is totally different. There are intelligent big data measurement systems as Waze (the "world's largest" community-based traffic and navigation app). Waze provides/sells real-time traffic and road info; then, it is possible to constantly updated travel time between two points and the path associated with this time. Based on Waze measurements it is possible to define travel time function, $TT_d(t, n_1, n_2)$, that indicates the average expected time for a trip from node n_1 to node n_2 , beginning at the moment t of the day d . This involves:

- The ability to resolve a new type of VRP problem with variable travel times, that it is not a trivial problem.
- Define models for re-routing and not for routing (starting from zero), since the optimization can be updated whenever an event occurs that changes the expected travel times, may be every second.

This new problem may be called VRP-TW-TDTT (Vehicle Routing Problem with Time-Windows and Time-Dependent Travel Times).

The processes enabled by intelligent measurement systems and by IoT (Internet of Things) and IIoT (Industrial Internet of Things) may be called Real-Time Optimization (RTO).

Abstract.

The chapter studies modeling of the transport service known as Less-Than-Truckload (LTL) Trucking.

The transport services market is very large, one of which is the so-called LTL that allows cargo dispatchers to use transport services partially using the load capacity of a truck. LTL can be defined as a global online marketplace for shipping services. Individuals and businesses advertise items they need to ship in a variety of categories, such as household items, pets, boats, or heavy industrial equipment, and carriers bid to carry the item. Until a while ago minor shipments to a truck (LTL) were seen as a problem. Then, an LTL network consists of a transport company with a fleet of trucks, which it serves is a sequence of delivery requests (received either by telephone, fax or internet) within a region.

The nodes of the network of operations are points at which the crew of the truck is relieved by another crew. When the shipping volume between two terminals is high, the company can offer a "direct service" between two HUBs: the trucks are fully loaded into the source HUB and completely unloaded at the destination HUB. This service usually involves regular operation with trucks traveling several times a week. For low frequencies, some shipments may experience unacceptably prolonged delays waiting for the truck to exit.

From an LTL network operator's point of view, the Request Selection Problem (RSP) is to choose the most cost-effective transportation service demands, for long-haul direct routes, or for multiple routes of collection and delivery; this may also include determining the bid price for requests or accepting an offer from the carrier previously agreed in a long-term agreement.

Mathematical modeling has two parts:

1. Operator must ensure the feasibility of the planned route that must comply with: i) the physical constraints of the system (e.g. travel times) and ii) business rules (e.g. attention windows, regulation, ...).
2. As a The goal the operator should maximize its profit by combining requests served, on one and/or multiple routes, based on a dynamic pricing strategy.

Therefore, a decision support system for the operator should be the result of studying how LTL conveyors should select/compete for LTL services on multiple hubs based on a dynamic pricing policy, which considers the dynamics of the LTL market and the dispatch of transport service commitments. Conceptually it must have the following models:

1. Demand Winning Offers, Machine Learning (ML) based on support vector machine (SVMs) to segment charge price offerings to load generators
2. Supply Winning Offers, Machine Learning (ML) based on support vector machine (SVMs) to segment price offerings to pay to carriers
3. LTL Network Dispatch and Revenue Management integrates the LTL network dispatch model and its link to the broker's revenue (Revenue Management).

More information in **Transport Revenue Management. Case: Less-Than-Truckload (LTL) Transport Networks**

<https://www.linkedin.com/pulse/transport-revenue-management-optimal-pricing-case-ltl-jesus-velasquez/>

Abstract.

More information in

- **Optimization of Logistics Operations in Ports**
<https://www.linkedin.com/pulse/optimization-logistics-operations-ports-jesus-velasquez/>



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Abstract.

This chapter contains the conceptualization of the decision-making process known as Timetabling Problem that belongs to a group of larger problems determined as "scheduling" problems. This generic problem has several application-specific cases such as scheduling games in a tournament, scheduling the operation of trains on a rail network, scheduling activities in universities/colleges among many others. It has been classified, by specialized literature, as an NP Hard problem. This means that as the dimensions of the problem increase, the solution time grows exponentially.

As a special case, which has received great attention from academic researchers and technology developers, is the Academic Schedule. Such is its degree of importance that since 1995, the Practice and Theory of Automated Timetabling (PATAT) Working Group, which belongs to the Association of European Operational Research Societies, has been working with the aim of sharing the progress made, and promote research and technological development to address this problem. Every two years PATAT conducts the International Series of Conferences on the Practice and Theory of Automated Timetabling attended by the community concerned: academics, data science professionals, and advanced analytics solution providers.

Scheduling problems can be defined, in their most basic form, with two entities: resources and activities. Its goal is to determine how resources should be used to perform activities in order to optimize the value of a performance indicator.

About time management, time-tabling problems can be classified into:

1. Discrete Time-Tabling: in which time is divided into periods and it is assumed that activities begin at the beginning of each period. To have periods of different length, it can assume a schedule in which activities can be performed, an activity can be realized during multiple periods. This is the case for university/college schedules.
2. Continuous Time-Tabling: in which activities can begin at any time; in this case the model determines when an activity begins and ends. This type of modeling is required for the coordination of industrial plants, ports, airports, transport activities, ...

The two approaches can give the same results, for this the discrete time problem must be divided into an "infinite" of periods to ensure the accuracy of the programming. The two problems are of the mixed programming type (MIP) and their complexity is NP-Hard. Only the discrete Time-Tabling case is discussed in this chapter applied to the optimization of the programming of academic activities.

More information in

- **University/College Scheduling - Time-Tabling Optimization**
<https://www.linkedin.com/pulse/universitycollege-scheduling-time-tabling-using-jesus-velasquez/>

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Abstract.

More information in

- **Human Resources Advanced Analytics**
<https://www.linkedin.com/pulse/human-resources-advanced-analytics-jesus-velasquez/>



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Abstract.



DECISIONWARE

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Abstract.

This chapter introduces:

- Design of a Decision Support System aimed at the administration and operation of smart grids.
- Integration of smart grids in energy efficiency projects
- Smart Grids Real-Time Distributed Optimization

The DSS is integrated by forecast models and optimization models oriented to support the decision making of:

- Electricity Agents Smart Grids
- Buildings/Homes Demand Response
- Industrial Energy Efficiency

The forecast models are:

- FRES - Forecast of Renewable Energy Sources
- FDEM - Forecast of Electricity Demand

The optimization models are:

- Smart Grid Economic/Regulated Dispatch:
- Smart Grid Unit Commitment
- Smart Grid Network Reconfiguration
- Smart Grid Network Design
- ETRM - Electricity Trading & Risk Management

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Abstract.

Demand attention is the driving factor of the supply chain activities. According to the requirements of the customers, the products that they eventually acquire are developed. Predicting demand with different time horizons is an expensive task, considering factors such as market volatility, competition, unforeseen events, price variations, economic events, marketing activities companies and others. In this chapter, interest is focused on aggregate demand for food products, with demand models being used to understand the aggregate market behavior by region, category and brand. In turn, it is necessary to know the possible behavior of the participation (market share) of brands and manufacturers in the different markets in which they participate.

The contents of the chapter are divided into the following numerals:

1. Market-Share Mathematical Modeling: Presents the theoretical/mathematical modeling foundations that support the advanced probabilistic models of a decision support systems.
2. FOOD-XPRESS case: a realistic case that describes the process of modelling the market based on a syndicated database, NIELSEN®, to carry out studies of: i) market potential and ii) FOOD-XPRESS market-share analysis.
3. Marketing Mix Optimization: describes the mathematical models used by FOOD-XPRESS to: i) determine the decisions to optimize the market share and to analyze the market equilibrium using Nash-Cournot games theory model.

This type of problem involves a significant computational effort as the amount of data to be processed in a real case can be classified as big-data. For example, to estimate market share for multiple suppliers (S), acting in multiple regions (R), selling multiple product categories (C); $S \times R \times C$ statistical models should be resolved simultaneously, with the following restrictions:

1. A common restriction that ensures that the sum of market share in $R \cdot C$ markets must be equal to 1, and
2. The market share of each supplier, in all $R \times C$ markets, should be greater than or equal to zero.

This problem corresponds to quadratic programming problem that represent constrained least squares models and are easy to model using Mathematical Programming.

A realistic case may have the following dimensions

V = 25 supplier/competitors

R = 50 regions

C = 1000 product categories

$S \times R \times C = 1'250.000$ Regressions

More information in: **Market Share Modeling Via Syndicated Databases - A Real-Life Case of Scientific Marketing using Nielsen Database**

<https://www.linkedin.com/pulse/market-modeling-via-syndicated-databases-case-jesus-velasquez/>

Abstract.

More information in

- **Revenue Management: Fundamentals**
<https://www.linkedin.com/pulse/revenue-management-fundamentals-applications-jesus-velasquez/>



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Mathematical Programming Entrepreneur and Researcher. Creator of:

Mathematical Methodologies:

1. **G-SDDP (Generalized Stochastic Dual Dynamic Programming)** an optimization methodology oriented to speed up the solution of large-scale problems, using distributed/parallel optimization.
2. **PDS (Primal-Dual Surrogate Algorithm)** an optimization methodology to solve mixed non-linear problems using the concepts of Surrogate Mathematical Programming.

Books:

1. **Mathematical Programming 4.0 for Industry 4.0 Cyber-Physical Systems** (book in edition and pre-sale)
2. **Large Scale Optimization Applied to Supply Chain & Smart Manufacturing: Theory & Real-Life Applications**, book of the series **Springer Optimization and Its Applications**. Main Editor.
3. **A Mathematical Programming Model for Regional Planning Incorporating Economics, Logistics, Infrastructure And Land Use**, Chapter 1 of the Book **Networks Design and Optimization for Smart Cities**. World Scientific Publishing Co Pte Ltd
4. **Análítica Avanzada: Estrategia para el Ordenamiento Territorial. Ciudades y Regiones: Inteligentes, Analíticas y Sostenibles** (libro en edición)

Advanced Analytics Technologies:

1. **OPTEX Optimization Expert System an Expert Optimization System** (a robot) that capitalize the experience in mathematical modeling and that generate Decision Support Systems in many technological platforms like IBM ILOG, GAMS, AMPL, MOSEL, AIMMS, C.
2. **OPCHAIN (Optimizing the Value CHAIN)** a collection of specialized solutions for optimize the value chain in general agroindustry supply chains, transport systems, energy systems (oil, gas, electricity), retail systems, logistics bank systems, financial and risk management, marketing optimization, mines and regional planning.
3. **SAAM (Stochastic Advanced Analytics Modeling)** cognitive robot specialized in applications of Machine Learning (Predictive Advanced Analytics: Support Vector Machines, Clustering, Artificial Neural Nets, Advanced Probabilistic Models and Optimization) using Mathematical Programming models.

Invited Keynote Lecture in: i) **XIX Latin-Iberoamerican Conference on Operations Research (CLAIO 2018, Lima)** and ii) 2nd (2017) and 3rd (2018) On-line International Conference on Ancient Mathematics & Science for Computing

Doctor in Engineering of the Mines Faculty of the Universidad Nacional de Colombia (2006). Industrial Engineer and Magister Scientiorum of the Universidad Los Andes (Colombia, 1975). Postgraduate studies in Planning and Engineering of Water Resources (Simon Bolivar University, Caracas) and in Economics (Los Andes University). Chair of CLAIO 2008. Consulting engineer with experience in management of projects in mathematical modeling, industrial automation and information systems, for large companies in multiples countries.

LOGYCA Award for Innovation and Logistic Excellence 2006 (GS1-Colombia). ACOLOG Award to the Investigation in Logistic (2006). Prize ACIEM-ENERCOL Award to Colombian Engineering (1998). ALBERTO LEON BETANCOURT Operations Research Award (1986). President of the Colombian Society of Operations Research (2000-2008). Vice-president of the Latin-Ibero American Association of Operations Research (2004-2008). Member by Colombia Executive Committee of the International Federation of Operations Research Societies (2002).

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