HUMAN BEHAVIOR MODELING: A STATE OF THE ART

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ABSTRACT

Over the last years, the study of Human Behavior Modeling was marked by a tremendous growth of interest from academics in several fields of application. Given the abundance of HBM techniques today applicable to model different human aspects, a review of the current state of the art has become essential. This work has as primary goal the investigation of the most common approaches – agent-based modeling, artificial neural networks, fuzzy logic, genetic algorithms, knowledge-based approaches, Markov chains and so on – as well as the newly applied techniques. Furthermore, the main advantages and limitations associated with implementing each analyzed methodology have been framed in order to provide some basic sparks in the identification of the most promising approach to model human behavior in different contexts.

Keywords: Human Behavior, State of the Art Analysis, Human Modeling, Human Centered Systems

1. INTRODUCTION

Human Behavior Modeling (HBM) is a disciplie with a great potential. In fact, HBM finds applications in numerous fields, such as disaster management (Agresta et al., 2015; Ardalan et al., 2015), military sciences (Mavor et al., 1998; Cordar et al., 2017) and manufacturing (Baines et al., 2004; Bocca et al., 2007).

Recent advances (in terms of research and technologies) permit scholars to publish innovative and new works on this topic. It is clear that modeling human behavior (HB) is very complex, not only for the uncertainty that affects human actions, but also for its strict dependence upon exogenous variables (weather, interactions with other people, etc.).

The key strength of the HBM is the opportunity to mitigate people's errors, satisfying and anticipating their needs, helping them in their daily actions (Cacciabue, 1998). Although such a scenario could be appear fantascientific, HBM practices are already used today to foresee HB during an evacuation, control human reactions while driving, reproduce people's social interactions and so forth. In addition, it is common opinion that HBM could be used to predict the future behavior of an individual (Liu and Pentland, 1999).

The ultimate goal of this article is to provide general knowledge about HBM issues, describing the state of the art and the major approaches to HBM. This paper explores, in the first section, the major approaches in HBM, which are identified and described, by underlining their possible advantages and disadvantages and providing some possible applications. In the second section, a brief reference to the recently approaches designed to overcome the limitations arising from the use of traditional methodologies is made. Finally, in the concluding section, after a careful and thorough analysis of all the studied approaches, remarks and future directions of this research field are outlined.

2. TRADITIONAL APPROACHES FOR HUMAN BEHAVIOR MODELING

Between the mid '50s and mid '90s, scholars designed several approaches to model HB. Seven approaches developed during this period have been identified and described in their main aspects in this section. At the end of section 2, a summary of the relevant advantages, limitations and solution to overcome limits is reported in table 1.

2.1. Knowledge-based

An important HBM approach is knowledge-based approach (KBA). The application of KBA consists nothing more than a "simple" IF-THEN algorithm. Applying this idea to HBM, this means that KBA models the behavior of people tha face with a limited number of situations and, whenever any of these happens (model using "IF condition"), they always respond with a preset action (specify in "THEN operation").

The ideal application field of KBA is in contexts characterized by a high degree of standardization; where an operator executes default actions as, for example, an assembly line (Embrey, 2005).

Numerous opportunities arise using the knowledge-based approach:

1. KBAs can be used as a training aid to increase the expertise of staff;
2. KBAs represent and efficient way of getting answers as it does not involve additional support staff: KBS are implemented by automated systems;

3. KBA model can be updated and extended easily: adding new lines in computer algorithm;

On the other hand, the KBA presents significant disadvantages. They depends by the static nature of a knowledge-based system (KBS).

1. KBSs does not learn from mistakes unless user feedback and human maintenance is part of its ongoing development;
3. KBSs not consider emotional aspects of HB;
4. KBSs not model path dependence;
6. Human-Decision Making (HDM) is very complex and hence it is impossible to describe it accurately by using a simple and static IF-THEN algorithms.

In general, the KBA is not suitable for HBM applications according with its numerous limitations: as already said, it is adapt manly for limited contexts. For this reason, following, some approaches less elementary are described.

2.2. Agent-based modeling

The Agent-Based Modeling (ABM) approach can be described with one word: interaction. Interactions with other people are the roots of human life. AMB becomes necessary when the system that we have to study is complex in terms of interdependence of its components.

The ABM approach is based on the concept of agent. For Macal and North (2005), there is no universal definition of the term "agent", though a number of features is identifiable and common to every definition as listed in Castle and Crooks (2006). These represents the main characteristic of an agent:

1. Autonomy: Agents are autonomous units, and they do not depend by other entities;
2. Heterogeneity: agents are different from each other;
3. Active: agents exert independent influence in a model;
4. Goal-directed: agents have a goal to pursue;
5. Reactive/Perceptive: agents are conscious of the existence of other agents, obstacles and surrounded environment;
6. Bounded Rationality: agents act solely on the basis of the information in their possession;
7. Interactive/Communicative: Agents have the ability to communicate with other agents and/or the environment within a neighborhood;
8. Mobility: Agents can move in the surrounding environment;
9. Adaptation/Learning: Agents can be designed to alter their state depending on their current state, permitting them to adapt with a form of memory or learning.

ABM is most natural method for describing a system composed of behavioral entities (Bonabeau, 2001). As Deljoo et al. (2012) said, it is flexible and it represents the canonical in disaster management. In this context, Bazghandi (2012) has written an work where he has explained the possible applications of ABM to manage emergences caused by a traffic jam, where he underling common point between agents' characteristic and HB in this context; or Castle and Crooks (2006) that propose a model to reproduce HB when people have to interface with hurricanes or sand dunes. Usually, in this application, agents modelled have to save themselves from dangerous event modeled.

Obviously, ABM has some limitations. People's actions and choices are often driven by irrationality that complicates the implementation and the development of a HB model. In adding, using ABM is impossible model human emotional aspects: fundamental for HBM (Elkosantini, 2016).

A number of application example in which some of the limitations have been solved above in terms of mathematical definition and simulation by ABM of human emotional aspects (e.g. fear, fatigue, stress, etc.) can be found in Bruzzone et al. (2011), Bruzzone et al. (2012), Bruzzone et al., (2014). Example of applications in non-typical contexts for ABM (cultural heritage fruition) can be found in Longo et al. (2014) and Longo et a. (2015).

2.3. Artificial Neural Networks

A good definition of Artificial Neural Networks (ANNs) is given in Holger and Mark (2008). In this work, the authors define an ANN as "a form of artificial intelligence which attempt to mimic the function of the human brain and nervous system".

ANNs have a well-defined structure. Fausett (1994) has described it as a set of elementary elements called neurons, units, cells or nodes. Each neuron is connected to other neurons by directed communication weighted links. The weights (a scalar number) determine the strength of the connections between the interconnected neurons and represent information used by the ANN to solve the problem studied.

ANNs are strictly connected with HBM problematics. In fact, they imitate human brain functioning: receiving from environment percepts in input and producing an action in output (Schmidhuber J., 2015). This is very important because brain represents the engine of human actions, and the knowledge of their hidden processes could be useful to understand the principles behind HDM. Unfortunately, the reproduction of neural processes in people is very complex: it represent a neuroscience problem − a modern discipline, where scholars have still much to discover .

In adding, making a comparison with ABM, we can observe that ANNs implementation is more complex and it requires a longer running time (ABM is described by linear laws, ANNs are described using non-linear laws). The propriety of non-linearity of ANNs permits the use of them in different application as the prediction of human motions (Abdel-Malek et al., 2016) or in smart environments (a set of software and hardware elements that support an intelligent interaction between environment and users) as in Dev (2001).

In conclusion of ANNs approach analysis, we try to explain them advantages/limitations. The advantages of ANNs use is, in Xu's opinion (2011):

1. An ANN can perform tasks that a linear program cannot: linear programs are less reliable than non-linear (such as ANNs);
2. When an element of the neural network fails, the network can continue working without any problem due to its parallel nature;
3. ANNs often exhibit patterns similar to those exhibited by humans;
4. An ANN learns and does not need to be reprogrammed.

On the other hand, ANNs' disadvantages are:
1. Handling of time series data in ANNs is a very complicated topic;
2. Once a network has been structured for a particular application, that network is ready to be trained. A possible way to do this is resort to the use of genetic algorithms (GAs);
3. ANNs foresee complex operation and, for this, the run of relative program is very expensive in terms of processing time.

2.4. Fuzzy logic
Fuzzy logic has been employed to handle the concept of partial truth, where the truth value may range between completely true and completely false by using decimal numbers. It is possible consider fuzzy logic as an evolution of traditional binary approach (also called crisp approach), where a specific model state is associated to variables that can assume only two values (0 or 1). The use fuzzy logic is recommended to model phenomena with a high grade of uncertainty: characterized by imprecise information and uncertain situations (Calvo-Florese et al., 2014). HBM is an example of this context, inasmuch HDM almost always are distinguished by a great number of possible action executable. In HBM, fuzzy logic is used as tool to HDM processes in mathematical formulas: for Kril and Yuan (1995) it provides us with meaningful and powerful representation of measurement uncertainties and also with meaningful representation of vague concepts expressed in natural language.
Some of most important opportunities arising from fuzzy logic use are describe below:
1. Enam et al. (2011) have proposed fuzzy logic to solve complex problems in neurosciences as it resembles human reasoning and decision-making;
2. In De Reus's opinion (1994) the application of fuzzy logic is very easy compared to computationally precise systems;
3. De Reus (1994) observed during an experiment that fuzzy logic models are not very sensitive to changing environments;
4. Fuzzy logic has proved to be suitable formalisms to handle imprecise/vague and uncertain knowledge (Cannon and Sied, 2004).

In the article by Cannon and Sied (2004), they also identify some disadvantages such as:
1. Fuzzy outputs can be interpreted in a number of ways, making the analysis difficult;
2. Fuzzy requires lot of data and expertise to develop a fuzzy system (Baines et al., 2004);
3. The use of fuzzy logic may often be sensible when computing power restrictions are too severe.

In addition, some other authors identified other important limitations, such as:
1. Fuzzy approach is based on stochastic assumptions (Sugeno and Yasukawa, 1993);
2. Differently to others approaches like ABM, fuzzy logic does not permit interaction between the different entities that populate the model (De Pedro et al., 2007).

It is important underline that, the previous limitations could be exceed joining ANNs characteristic at fuzzy logic propriety: recusing at the neuro-fuzzy logic approach.

2.5. Neuro-fuzzy logic
Neuro-fuzzy logic approach represents a "trait d'union" between ANNs and fuzzy logic. This approach captures the essential aspects of the two methods. Neuro-fuzzy logic uses fuzzy logic theory to describe the uncertainties associated with HB, such as thinking and reasoning, while the use ANNs permit to model important human characteristics as learning, adaptation, fault tolerance, parallelism and generalization.
Neuro-fuzzy logic is used in HBM to overcome limits of fuzzy logic and ANNs. Acampora (2015) used it to limit uncertainty and vagueness that characterize HBM fuzzy logic applications, proposing a model that reproduce the dependence of HB to the external context's modification (including learning propriety of ANNs). Neuro-fuzzy logic have some interesting characteristics (Acampora, 2015):
1. Easy to implement fuzzy natural languages so that the structure of knowledge is very clear and efficient;
2. Any changes in the task and environment can be easily taken care of by adapting the neural weights;
3. Since a fuzzy system is one kind of interpolation, drastic reduction of data and software/hardware overheads can be achieved.

It is important say that, neuro-fuzzy logic approach is a much discussed method in the academic field. In fact, some scholars have doubts about the quality of the system (Acampora, 2012). In particular, scholars are investigating about the compatibility between ANNs and fuzzy logic (Acampora, 2012).

2.6. Genetic Algorithms
Often, people have to reach different objectives in the same time. This situation is not expected by previous described approaches and, to overcome this limit it is possible use GAs approach.
GAs are inspired by Charles Darwin's evolutionary theory. The basic techniques of GAs are designed to emulate evolutionary processes in real world. In a GA, a population of candidate solutions to an optimization

problem is evolved toward better solutions. Each candidate solution has a set of properties (called chromosomes) which can be altered. GAs represent a good method to model HB. Indeed, they allow to model situations where the entities implemented in the model studied must pursue different objectives simultaneously (multi-objectives problems). For this reason, GAs could be a good way to model human-decision making (HDM) processes, for their greater adherence with reality. Numerous opportunities arise using the GAs approach. Below, we have tried to explain the most important:

1. GAs have the ability to avoid being trapped in local optimal solutions, unlike traditional methods, which search from a single point (Deepa, 2007);
2. GAs permit solving optimization problems where we have to maximize/minimize more than one parameter (Tabassum, 2014);
3. Noisy/stochastic objective functions are handled very well (Deepa, 2007);
4. A large number of parameters can be a problem for derivative based methods (Deepa, 2007).

On the other hand, GAs also have some limitations:

1. GAs resolve multi-objective problems. In this type of models sometimes reaching an optimal solution is impossible: optimizing an variable value could damage another parameter;
2. GAs usually need a decent sized population and many generations before you see good results.
3. GAs' solutions strictly depend from a fitness function: a poorly designed fitness function could be make ambiguous results.

A possible application of GAs is in knowledge management field. Kosorukos (2001) has defined a GA applied to this purpose Human Based Genetic Algorithm (HBGA), that is possible use in different contexts as brainstorming and innovation management to find the best solution during a discussion or a better marketing strategy of a new product.

2.7 Markov Chains

A possible application of Markov chains is in HBM fields, in particular to predict HB with an high accuracy. A formal definition of Markov chain is provided by Luenberger (1979): "An n^{th}-order Markov chain process is determined by a set of n states $\{x_1, x_2, \ldots, x_n\}$ and a set of transition probabilities pij, i =1,2, ..., n, j=1, 2, ..., n. The process can be in only one state at any time instant. If at time k the process is m state s_i, then at time k+1 it will be in state x_j with probability p_{ij}"

HB is amenable to them imagining that, at a precise moment, an individual (α) is located in an initial state xo associated with a specific behavior. In this situation, α may carry a limited range of actions $\{x_1, x_2, ..., x_n\}$. The approach of the Markov chain consists of assigning a probability that quantifies the possibility that α has to move from x_o to a generic state xi, executing a particular operation, as Liu and Pentland (1999). The same structure is presented by Dongyue et al. (2016), where the authors predict interarrival time of visitors in a library using Markov chains. From reading many studies about the use of Markov chains, it is possible identify the main benefits that they generate in HBM applications:

1. Markov models are relatively easy to derive (or infer) from successional data;
2. Markov chains approach has high reliability. For instance, the model proposed by Pentland and Liu (1999) has a reliability of 95%);
3. Results of the analysis of Markov models are readily adaptable to graphical presentation;

On the other hand, the Markov approach also has some limitations. For instance, Markov chains is based on uncertainty and approximated data; it is impossible using them model human interactions and they do not integrate learning. In addition, considering that Markov chains have a prediction interval limited to a few seconds (Liu and Pentland, 1999), it is possible make from this limitation an opportunity: this HBM approach could be used to model hasty decision for it capacity to reproduce in a faithfully way the operations of an individual in a very short period. Before analyzing some recently proposed approach, table 1 reports a useful summary of the methods described in section 2.

3. MODERN APPROACHES FOR HUMAN BEHAVIOR MODELING

Since 2013 various scholars have been developing new and interesting methodologies that break with the past. This section will analyze five new approaches:

1. Ambient Intelligence (AmI) (Botìa, 2014): Ambient Intelligence (AmI) is an emerging discipline in information technology, in which people are empowered through a digital environment mainly consisting of complex software and devices (sensors and actuators) connected through a network;
2. Data-driven (Oliver, 2015): The Data-drive approach consists in the modeling of HB using data collected from mobile phones. The use of data driven approach investigates the personality of individuals, something that other HBM methods do not;
3. Dynamic factors (Abebe, 2016): This approach offers a better model of evacuee behavior than traditional methods, which do not adequately account for the numerous dynamic factors that would notably influence evacuation decisions of individuals. It is important underline that Dynamic Factors approach was applied only for evacuations, and needs improvement that makes it applicable in other contexts;
4. Human-Centred System (HCS) (Elkosantini, 2016): the main advantage of HCS is that it considers psychological, individual, and social factors, in contrast to others traditional approaches, but the method is not yet validated;

Table 1. Traditional HBM approaches – a synthetic description

APPROACH	CONTEXT WHERE USE IT	RELEVANT ADVANTAGES	RELEVANT LIMITATIONS	SOLUTIONS TO OVERCOME LIMITS
AGENT-BASED MODELING	**CONTEXTS WHERE THERE ARE PEOPLE WITH A HIGH GRADE OF INTERACTION AND HETEROGENEITY.**	Capture emergent phenomena [17], [9]. Provide a natural description of a system [12]. **FLEXIBILITY [21].**	It is very difficult to model human psychology, when it is train by irrationality [17]. **ABM USES MATHEMATICAL RELATIONS RARELY USED IN THE REAL WORLD [17].**	**MODERN APPROACHES**
ARTIFICIAL NEURAL NETWORKS	Contexts where it is not possible to identify some relations between input and output **CONTEXT WHERE WE HAVE TO MIMIC THE HUMAN DECISION- MAKING PROCESS.**	ANNs preforms better than linear program [45], [44]. ANNs is a black box like human brain [1], [44]. **ANNS LEARN AND DOES NOT NEED TO BE REPROGRAMMED [44]**	The non-linear quality of ANN makes it difficult to apply this approach [44]. ANNs need to train [39]. **ANNS FEEDS ITS OUTPUTS BACK INTO ITS OWN INPUTS [37].**	Genetic Algorithms Neuro-fuzzy Logic **MODERN APPROACHES**
CRISP APPROACH	**CONTEXTS WHERE PEOPLE HAVE TO CHOOSE BETWEEN ONLY TWO ALTERNATIVES.**	Simple application [16]	**POSSIBILITY TO MODEL ONLY TWO ALTERNATIVES [16].**	Fuzzy Logic Neuro-fuzzy Logic **MODERN APPROACHES**
FUZZY LOGIC	Contexts where people have to choose between more than two alternatives. **SITUATION CHARACTERIZED BY UNCERTAINTY.**	Fuzzy logic resolve complex problems [26]. Simple application [24]. Fuzzy algorithms are robust [24] **LIMITS AMBIGUITIES [15].**	It is tedious to develop fuzzy rules and membership functions [15]. Performances of fuzzy model are straightly connected with calculator specifics [15]. **FUZZY LOGIC IS BASED ON STOCHASTIC ASSUMPTIONS [15].**	Agent-Based Modeling Dynamic Factors Neuro-fuzzy Logic **MODERN APPROACHES**
GENETIC ALGORITHMS	Contexts where there are more than one objective to pursue. **CONTEXTS WHERE WE HAVE TO TRAIN ANNS.**	It is possible to use GAs to model multi-objective problems [20], [43]. **A LARGE NUMBER OF PARAMETERS CAN BE A PROBLEM FOR DERIVATIVE BASED METHODS [17]**	No guarantee of finding a global maxima. **SOLUTIONS OF GAS DEPEND ON THE FITNESS FUNCTION.**	Neuro-fuzzy Logic **MODERN APPROACHES**
KNOWLEDGE-BASED	Contexts where we can easily code facts and rules. Contexts describable by standardized procedure. Context sufficiently restricted. **CONTEXT WHERE WE DO NOT FIND AN EXCESSIVE NUMBER OF EXCEPTIONS.**	Easy to traduce in computer languages. The knowledge base can be updated and extended easily. **KNOWLEDGE BASE CAN BE UPDATED AND EXTENDED EASILY.**	Does not learn from mistakes unless user feedback and human maintenance is part of its ongoing development. Unlikely to come up with creative solutions. Not able to learn from mistakes. **CANNOT CREATIVELY COME UP WITH NEW SOLUTIONS FOR ISSUES.**	Agent-Based Modeling Artificial Neural Networks Fuzzy logic Neuro-fuzzy Logic **MODERN APPROACHES**
MARKOV CHAINS	Contexts where there are heterogeneous agents. **CONTEXTS WHERE WE HAVE TO MODEL HIDDEN ASPECTS THAT WE CANNOT OBSERVE DIRECTLY.**	High reliability (95%). [33] **RESULTS OF THE ANALYSIS OF MARKOV MODELS ARE READILY ADAPTABLE TO GRAPHICAL PRESENTATION.**	Impossible to model interactions. Based on stochastic laws. **MARKOV CHAINS HAVE A PREDICTION INTERVAL LIMITED TO A FEW SECONDS [33]. MARKOV CHAINS DO NOT INCLUDE LEARNING PROPRIETY [10]**	Agent-Based Modeling Dynamic Factors **MODERN APPROACHES**
NEURO-FUZZY LOGIC	**CONTEXTS WHERE FUZZY LOGIC AND NEURAL NETWORK ARE NOT SUFFICIENT TO DESCRIBE SITUATION.**	High scalability. [3] Detection human behavior in a complex scene [3]. **DRASTIC REDUCTION OF DATA AND SOFTWARE/HARDWARE OVERHEADS CAN BE ACHIEVED [3].**	Limitation of Fuzzy Logic and ANNs approaches [3]. Doubts about quality of approach. [3] **COMPATIBLY BETWEEN FUZZY LOGIC AND ANNS. [39]**	Agent-Based Modeling Genetic Algorithms Modern approaches

5. Video Analysis: Video analysis or, for Asafar et al. (2015), Automatic visual detection approach, is the analysis of HB using systems of video capture such as video surveillance. It is possible used video analysis as tool to collect information to build models.

As a result of the analysis conducted in this article, some conclusions can be drawn about the current status questions of HBM: first, there is a substantial number of HBM approaches, and all have their advantages and limitations. From this it is clear that it is impossible to define an optimal approach to HBM. However, it is possible to define a target for which the application of a specific approach can be particularly recommended. Table 1 presents a scheme with this information, with an indication of possible solutions to surpass the limitations of the various approaches. An analysis of these reveals that the ABM approach solves the majority of other HBM methodologies' limits. This is endorsed by the fact that ABM is a flexible approach that is widely used in many different contexts.

4. CONCLUSIONS

This paper is an attempt to provide the reader with useful state of the art information about the past and current research activities in the area of Human Modeling Behavior. After surveying the most known traditional methods the article reports a brief summary about the modern approaches, where Agent Based Modeling seems to present the major advantages because:

1. It allows the modeling of interactions among the various entities that make up the model;
2. The agents have the characteristic of being able to learn;
3. All actions of agents are aimed at a specific purpose.

Obviously, there is no denying the presence of handicaps also in modeling agents. Such restrictions can only be reduced by using recently developed methods, but they are still at an early stage. Further research activities are therefore needed to carry out VV&A (Verification, Validation and Accreditation) with the aim of solving current flaws and increasing the reliability of the proposed approaches.

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Letizia Nicoletti is CEO of Cal-tek Srl from 2012 to 2014 and she is currently Senior Manager at CAL-TEK. She obtained her Bachelor Degree in Management Engineering, Summa cum Laude, her Master Degree in Management Engineering, Summa cum Laude as well as her PhD in Mechanical Engineering from University of Calabria, Italy. She has followed as Scientific Responsible many research projects in different areas including logistics and distribution, Defense and Cultural Heritage. She was also the main Responsible for all the services provided by CAL-TEK to NATO STO CMRE.

She carried out several work experiences travelling in Europe and United States working as CEO of Cal-tek Srl and attending Conferences and Workshops in the M&S area. Moreover, since 2011 she has been actively involved in the organization of the International Multidisciplinary Modeling and Simulation Multiconference (I3M), one of the major events in the field of Modeling Simulation worldwide.

Since 2009 she has acquired a strong experiences in software development and Modeling & Simulation (M&S) including High Level Architecture (HLA) and Distributed Real Time Simulation. Her skills include requirements definition and development, conceptual modelling, model simplification, data collection and analysis, representing unpredictable variability and selecting statistical distributions, models and software coding, experimentation, verification and validation, serious games development, visualization, simulation software.

Antonio Padovano is PhD student at the University of Calabria where he received his degree in Management Engineering summa cum laude.

His work focuses on the development of interoperable discrete event and agent-based simulations for decision support in complex systems in the area of Industry, Logistics and Defense with a particular attention to Human Modeling & Simulation to reproduce the main functions of human behavior in order to assess the impact of human choices, decisions and actions. He participated to different research projects both in cooperation with MSC-LES and CAL-TEK Srl (e.g. T-ESEDRAS, SMARTDISTR, SG-ICT).

He participated to different international conferences (EMSS, MAS, HMS, China-Italy Science, Technology and Innovation Week, etc.) and he also served as Advisor for University of Calabria students at ICAMES 2016 (Istanbul, Turkey).

He was visiting student at the Business School at Rutgers University (The State University of New Jersey, USA) between June and September 2015 working in the field of simulation modeling and development aimed at analyzing and improving the performance of supply chains and industrial systems, in particular, container terminals as well as implementing a software tool whose main objective is to support decision making processes within complex industrial and logistic systems in order to evaluate green management practices in terms of both environmental impact.

He teaches as tutor for undergraduate and graduate students enrolled in the Degree in Mechanical Engineering at the University of Calabria in the classes “Industrial Systems” and “Industrial and mechanical systems”.

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Marco Vetrano received his degree in Computer Science at University of Calabria. His field of expertise covers IT Platforms, Programming Languages (C++, VC++, C#, Java, Visual Basic, VBA, SQL, T-SQL, HTML, XML, PHP, JavaScript, Lua, Python), Databases Design and Management (SQL Server, Oracle, MySQL, MS Access, Hadoop, YARN) and Operating Systems (Microsoft Windows, Macosx, Linux).

He is currently working as CTO at CAL-TEK srl, a spin off company of University of Calabria supervising the development of products solutions.

Marco Vetrano gained great experience regards Mobile Application Development for Web platform with implementation of advanced graphics, detection and management of users’ location, and various types of interaction with remote servers.

He is expert of Graphic Interface Development (Unity3D, Vega Prime), UML Design and Development Environments (Eclipse, Netbeans e Xcode).

He has been fully involded in different research project (e.g. SIMCJOH, SG-ICT) also working in cooperation with international partners such as CAE, NASA KSC, Selex-ES, University of Bordeaux.