GREEN LOGISTICS – THE CONCEPT OF ZERO EMISSIONS PORT'S ENERGY MANAGEMENT

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ABSTRACT: The mean logistics refers to the transport, storage and handling of products moving from raw material, through the entire production procedure to their end point of sale or consumption. Logistics is responsible for a variety of externalities, including air pollution, noise, accidents, vibration, land take and visual intrusion. Ports are a key element to the supply chain and green logistics are of primary interest. In this paper, we propose an effective and sustainable framework for ports which focus in Zero emissions and sustainable ports operations and development.

INTRODUCTION

Ports are a key element to the supply chain and green logistics are of primary interest. The concept of zero emissions' port refers to a port powered mainly by renewable energy. In order to fulfil its power requirements and to reduce the air emissions, ports are using this concept for the emerging cold iron regulation. Several renewable energies, their application to port operation and the way that several smart grid algorithms can enhance the overall performance are discussed. The concept of smart grid is used in order to facilitate the use of several renewable energies and to monitor and control all demand and distribution of port energy systems. Several examples will be presented mainly from European and South Asia ports related with shore energy and how the energy management could be improved using renewable energies facilitated by advanced algorithms for energy management. The paper will also discuss simulation results of energy management algorithms (like Particle Swarm Optimization) and their limitations.

REVIEW

The theoretical framework of the present work includes the areas of green supply chain, logistics, port and intelligent methods of energy management.

Green supply chain management

Green supply chain management which especially focuses on environmental aspect of sustainability, can be influential on reaching a sustainable supply chain (Sarkis et al., 2011). It focuses on environmental aspects of designing a supply chain which is one of the aspects of a sustainable supply chain (Guang shi et al., 2012). It can also decrease environmental impacts, in supply chain (Darnall et al., 2008).

Green supply chain management which integrate environmental concerns with supply chain management, control environmental impacts of products in its life cycle besides reducing supply chain's energy consumption (Zhu et al., 2017). Green supply chain management includes green design as an approach for increasing product quality while considering environmental aspects of a product (Mohtashami et al., 2020).

The next figure shows the critical factors of green supply chain management:

Figure 1: The critical factors of supply chain management (https://link.springer.com/)

Green logistics

Green logistics describes all attempts to measure and minimize the ecological impact of logistics activities. This includes all activities of the forward and reverse flows of products, information and services between the point of origin and the point of consumption (Grant et al., 2017):

Figure 2: The main concept of green logistics (wgeco.org)

The Benefits of green supply chain through green logistics are (Grant et al., 2017):

- Green Supply Chain.
- Positive impact on financial performance.
- Sustainability of Resources.
- Lowered Costs/Increased Efficiency.

- Product Differentiation and Competitive Advantage.
- Adapting to Regulation and Reducing Risk.
- Improved quality and products.

Green Ports

Port research has also increasingly addressing ecological issues. Darbra studied 26 European ports' requirements for environmental information via interviews. The major environmental parameters that ports required to be monitored were marine related issues, water quality, meteorological parameters, turbidity and sediment processes. One of the major environmental impacts generated by ports in air pollution and there are several studies which specifically addressed this aspect (Darbra et al., 2009). Liao analysed the impact of using Taipei Port in Taiwan on the carbon dioxide emissions CO_2 of inland container transport (Liao et al.,2010). In additions to CO_2, dominate emissions from ships at ports include SO_2, NO_x, PM_{10}, $PM_{2.5}$, HC, CO and VOC. The health effects to residents of the local community include asthma, other respiratory diseases, cardiovascular disease, lung cancer and premature mortality (Bailey and Solomon, 2004).

Another major environmental concerns is water pollution and the effect on marine ecosystems. Water pollution comes from ballast water, fuel oil residue and waste disposal from ship operations as well as cargo residue. The need for upgrading and maintancnce of navigation channels at port waters would lead to contaminated sludge from dredging. There may also be a need to alter the sea floor and natural geographical feature causing disruptive impact on marine ecosystems due to dredging and civil works (Peris-Mora et al., 2005).

The next figure (Fig.3) shows the Smart grid for zero emission's port concept. The concept of "*smart grid*" defines a self healing network equipped with dynamic optimization techniques that use real time measurements to diminish network losses, sustain voltage levels, rise reliability, and improve asset management. The smart grid first hang on identifying and researching crucial performance measures, designing and testing suitable tools, and developing the proper education curriculum to equip current and future personnel with the knowledge and skills for deployment of this highly advanced system (Momoh, 2012).

Specifically, a control and distribution center is fitted with a number of renewable energies namely offshore wind turbines, PV sources for the park or from the buildings, wave or tidal energy depending of port potential and geothermal energy according to ports abilities. The center is connected with permanent electric grid used according to the needs and a digital metering system (in several areas such as docks and port's facilities) in order to monitor the port's energy demand and so to distribute the required available electrical power. The excessive power produced from renewable sources is transformed to hydrogen or stored in new technologies high capacity batteries (Nikitakos et al., 2019).

Specifically, the Hydrogen production is the family of industrial methods for generating hydrogen. There are four main sources for the commercial production of hydrogen: natural gas, oil, coal, and electrolysis; which account for 48%, 30%, 18% and 4% of the world's hydrogen production respectively. The production of hydrogen plays a key role in any industrialized society, since hydrogen is required for many essential chemical processes.[4] As of 2019, roughly 70 million tons of hydrogen are produced annually worldwide for various uses (Roman et al., 2008, Häussinger et al., 2011).

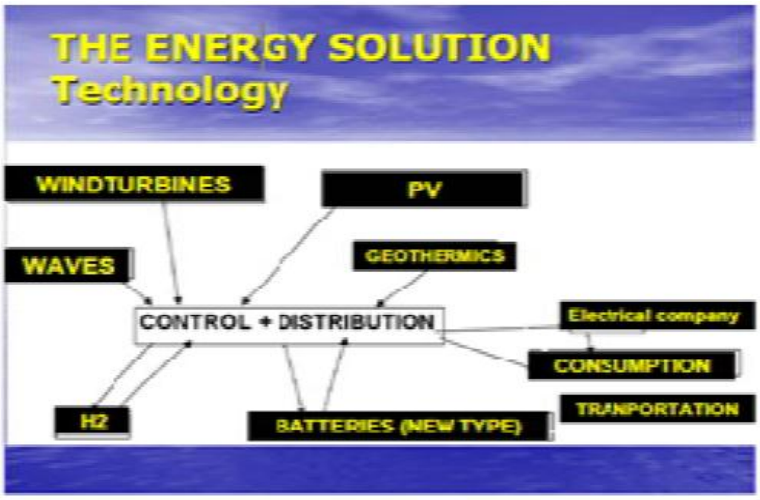

Figure 3: Smart grid for zero emission's port concept (Nikitakos et al., 2011)

Intelligent Methods for Energy Management

Many researchers have been proposed intelligent techniques in order to perform efficient energy management in systems with multiple loads and multiple sources. In the literature, these techniques are divided into two main categories. In the first category the approaches confront the physical problem by applying a central control scheme while in the other category the approaches use a decentralized control scheme.

Considering the central energy management, Huang & Liu have been proposed a neural network for energy management in residential applications. The network learns from the environment and is adapted according to the user's needs. Energy management mainly involves charging and discharging of a battery that is connected to the public power grid. The neural network decides when the battery should meet the energy needs of the user, when has to charge and when has to discharge by injecting power into the public grid. The disadvantages of this approach are that the network decides considering only economic benefits and that the energy management lies on controlling only a battery. The advantage of this network lies on its ability to learn online and improve its behavior under real conditions (Huang and Liu, 2013).

Rasheduzzaman and others have been proposed a hierarchical energy management scheme with a central coordinator in grid connected microgrids. The central coordinator is able to identify when microgrid operated in island or grid connected mode. The central coordinator gathers information from the local controllers of the distributed sources and after the data analyzation control signals are transmitted back to the controllers in order to maintain power balance. The main advantage of this method is its simplicity as the energy balance is succeeded by controlling only the distributed sources. The disadvantage of this method is that the central coordinator does not have access to electrical loads information and sudden changes in demand could cause the microgrid to collapse. Also, the central coordinator had no learning or adaptation mechanisms and cannot deal in any changes of the microgrid topology (Rasheduzzaman et al., 2012).

Zaidi and Kupzog have been proposed an energy management system consisting of a central controller which controls both loads and battery to assure energy balance at peak times. The advantages of this method are that the central controller has the ability to reduce the overall electrical load according to predefined priorities and additionally, it uses acquired old data to make forecasts concerning the energy demand profile. The disadvantage of this method is that this framework has no learning mechanism for adapting its strategy and decisions are only based on predefined priorities and forecasting energy demand (Zaidi and Kupzog, 2008).

Kuznetsova et al. have been proposed a Q-learning algorithm with a two-step ahead horizon for energy management of a grid connected wind generator system, which composed by a battery, a variable electrical load and a wind generator. The energy management is based only in the battery scheduling. The underlying framework is a multi-criteria decision-making framework by one single consumer, which aims to increase the battery usage during high electricity demand and increase the usage of the wind turbine for local use so as to increase consumer independence from the public electricity grid. Predictions regarding the available wind power and load demand are introduced into the Q-learning algorithm in order to the optimal battery actions to be selected.

Leo and others have been proposed a similar approach for energy management of a photovoltaic system using a Q-learning algorithm with three-step ahead horizon in order to schedule the battery usage. The photovoltaic system consists of a local consumer (variable electrical load), a photovoltaic source and a battery. The Q-learning algorithm was used to optimize the battery scheduling in dynamic environments by taking into consideration solar power and load. The main advantage of both approaches is that they use central control framework with learning mechanism for minimizing the system independence from the public electrical grid and can easily adapt their behavior in any changes. The disadvantage of these approaches is that the energy management system is tested in a simple system (small state-action space) and is not tested in more complex systems with higher number of state-action combinations. Additionally the actions of the algorithm are only two concerning the battery charging/discharging (discrete) and cannot perform actions of partially charging or discharging (Leo et al., 2014).

François-Lavet and others have been proposed a deep reinforcement learning framework for energy management of storage units in a photovoltaic system. The problem of optimal management of a single hydrogen unit has been formulated as a decision-making problem which uncertainties are introduced at each time instant by the stochastic energy demand and the stochastic energy production of the photovoltaic source. The deep reinforcement learning architecture was used to extract knowledge from previous production and consumption time series and to give each state values in the three discrete actions of the hydrogen unit (maximum charge, maximum discharge and inertia). The advantage of this approach lies on the learning mechanism which can adapt the behavior of the management system in changes. The disadvantage of this approach is that the energy management system is tested in a simple system and the actions of the algorithm are only three concerning the hydrogen unit (François-Lavet et al., 2016).

Considering the decentralized energy management, some researchers have been proposed a multi-agent system with four agents, each one with specific responsibilities. The control agent monitors critical measurements of the grid and decides for the islanding or grid connecting operation, the agent of the electrical sources who decides about the amount of the produced energy, the user agent who decides the priority of the electrical loads according to the user preferences and the database agent that stores and distributes information to all agents. The advantage of this method is that the computational burden is distributed amongst the agents but the agents functions are predefined and decisions are made considering the current state of the microgrid without any scheduling (Pipattanasomporn et al., 2009).

Chung and others have been proposed a multi-agent system with local agents and a central coordinator for optimal response to emergency power demand. This approach proposes a control framework where each agent controls a distributed source or programmable load and there is a central coordinating agent who coordinates the local agents. In cases of high demand from the electrical public grid, the central coordinator checks the availability of each resource and sends audit commands to local agents. This method distributes the computational load but the control framework cannot be considered fully decentralized as it relies on the use of a coordinator. Failure of the coordinator will lead to entire collapse of the system. This method also relies on predefined functions without any learning mechanism and no scheduling is provided (Chung et al., 2013).

Li and others have been proposed a multi-agent based model for energy management. The system consists of eight production units, eight loads and eight agents. Each agent is dedicated to a unit and a load. Four of the eight agents do not control their units or loads (considered uncontrollable) and simply record measurements and share information with the other agents. The other four agents by taking into account both their own gathered information and the sharing information, decide whether to increase or decrease the output of their units in the next time step according to predetermined rules. The proposed method is considered to be completely decentralized and in any failure the system will continue to partially operate but this method has no adaptation or learning mechanism and cannot adapt in changes of the microgrid (Li et al., 2016).

Logenthiran and others have been proposed a multi-agent system for power generation planning and energy management. The system consists of eight different types of agents, separated by their operation. There are distributed agents who are responsible for the levels of production of distributed sources, there are load agents that control the consumed power in loads, there are renewable energy agents that control the levels of renewable energy production, there are storage agents that decide the storage and the delivery of energy from the storage units, there is an agent who forecasts the demand, there is an agent who communicates with the agents of the distributed sources and makes provision for power generation and finally there is a central agent coordinating the entire microgrid. The control framework balances the power between modules and also performs storage scheduling in order to increase the reliability of the microgrid. However, the agents do not contain a learning mechanism and cannot adapt their behavior in changes and the framework cannot be described as fully distributed. Failure of the central agent causes failure of the entire system (Logenthiran et al., 2012).

Kyriakarakos and others have been proposed a multi-agent system for power management of a stand-alone residential grid by shedding loads. The system consists of four control layers. In the first layer the agents make a simple provision for the production of the renewables sources. In the second layer there is only one agent who decides whether further loads should be shed. In the third layer there are many agents each one dedicated to one home. They receive information from the second layer, from the neighboring agents and from the local agents in the fourth layer. On the basis of this information, they decide whether to shed further loads. In the last layer, each agent is dedicated to a group of loads, such as lighting loads, cooling loads etc. and decides which loads to shed based on the information which receives from the third layer. This approach achieves high reliability but the proposed control framework has no learning mechanism as all agents perform predefined functions and no scheduling is performed. Also, the multi-agency system is not decentralized but follows a hierarchical structure (Kyriakarakos et al., 2013).

ANALYSIS

Based on the literature review the macro-environment for a typical green port (Zero emission), it shows the next figure (Fig.4). It comprises of basic layers:

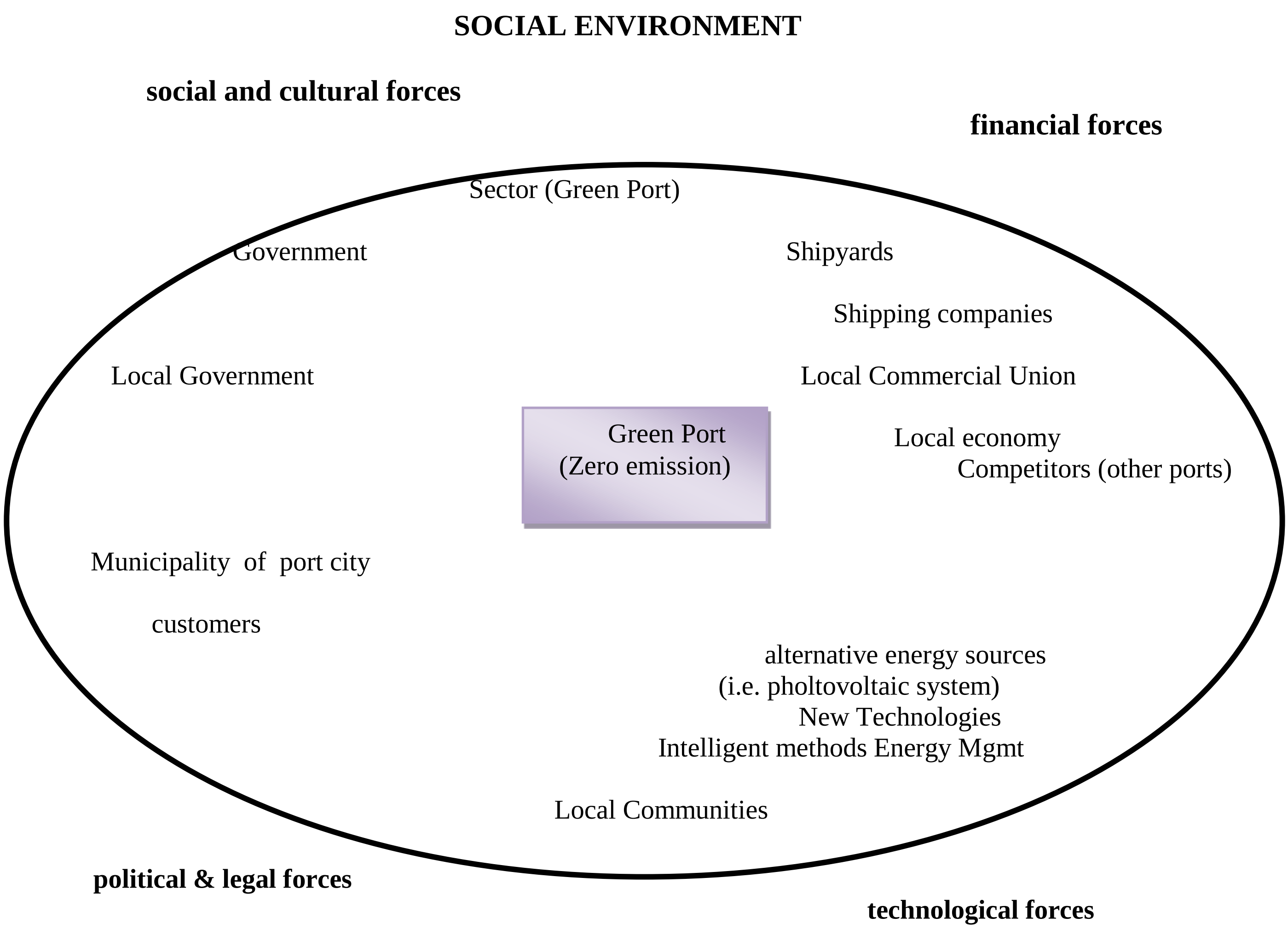

Figure 4: Macro-environment analysis by authors

Specifically, we use the PESTEL (Political, Economic, Social, Technological, Environmental and Legal) is used to describe a typical green port (Zero emission) macro-environment analysis based in intelligent methods of energy management (Tab.1):

Table 1. PIESTEL Analysis by authors

POLITICAL	ECONOMIC	SOCIAL	TECHNOLOGICAL	ENVIRONMENTAL	LEGAL
Taxation (high taxation is disadvantage) Energy policies (friendly in environment) Political stability	GDP Investments in alternative energy sources (i.e. sun, air etc.) Local economy & Commercial Unions	Living condition in city of port is difficult (air pollution, etc.) the local community is receptive to environment	Research & Technology (exploitation of new technologies i.e. Artificial Intelligence etc.)	the natural environment near the port is in danger (marine pollution, air pollution etc.)	Environment protection laws unsatisfactory protection for constructions and the natural environment

Based in review (green logistics & port, intelligent methods for energy management) and PESTEL analysis, we propose a Intelligent Energy Management and Green Port framework (follow the Green and sustainable port framework of Lam & Van de Voorde, 2012), as shown the next figure

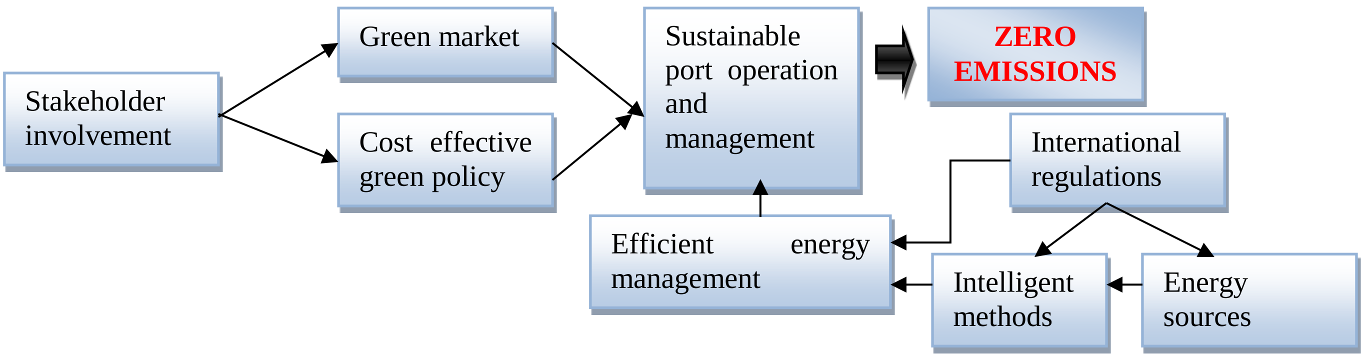

Figure 4: Intelligent Energy Management and Green Port framework (IEMGPF) by authors

CONCLUSIONS

Ports are a key element to the supply chain and the green logistics are of primary interest. The concept of zero emissions' port is referred to a port powered mainly from renewable energies in order to fulfill its power requirements and to reduce the air emissions. The IEMGPF is effective and sustainable framework for ports which focus in Zero emissions and sustainable ports operations and development.

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