Chapter 1

An agent-based simulation model for energy saving in large passenger and cruise ships

1.1 Introduction

Undoubtedly, energy saving is of paramount importance in the shipping industry, as far as both the protection of environment and the reduction of the associated operating costs are concerned. In this direction, the International Maritime Organization aims to reduce ship emissions by at least 50% by 2050, while ships to be built by 2025 are expected to be a massive 30% more energy efficient than those built some years ago [IMO, 2018].

A particular ship category is that of large passenger and cruise ships, which reportedly consume a large amount of energy and thus constitute an interesting area for investigating diverse energy consumption and energy saving solutions. It is estimated that a large ship burns at least 150 tons of fuel per day and emits more sulphur than several million cars, more NO2 gas than all the traffic passing through a medium-sized town and more particulate emissions than thousands of buses in London [Vidal et al., 2016]. While the cruise ship industry starts taking its first steps towards an emission-free cruise, cruise travels are among the most carbon intensive in the tourism industry; the contribution of the cruise industry to global CO2 emissions was estimated to 19.3 Mtons annually in 2010 [Eijgelaar et al., 2010].

To the best of our knowledge, while energy saving solutions have been thoroughly investigated in the case of (smart) buildings, very limited

research [Barri et al., 2020a] [Barri et al., 2020b] has been conducted so far for the abovementioned ship category. Aiming to contribute to this research gap, this chapter reports on the development of a novel approach that builds on a sophisticated agent-based simulation model for the management of diverse energy consumption issues in large passenger and cruise ships. The model takes into account the size, characteristics (e.g. age, special needs etc.) and behavior of the different categories of passengers onboard, as well as the energy consuming facilities and devices of a ship. The application is generic enough to cover requirements imposed by (i) different types of vessels, by taking into account detailed spatial data about the layout of the decks of a ship and the associated position of the energy consuming devices and facilities; (ii) alternative ship operation modes, corresponding to cases such as the ship being cruising during day or night, or being stopped at a port; (iii) different passenger groups in terms of their size and behavior, by considering that the energy consumption of many devices or facilities (e.g. restaurant, air condition etc.) depends on the number of passengers in or nearby them. The proposed agent-based simulation model has been implemented with the use of the AnyLogic simulation software (https://www.anylogic.com/), which provides a nice graphical interface for modeling complex environments and allows the extension of its simulation models through Java code.

A novelty of our approach concerns the exploitation of the outputs obtained from multiple simulation runs by prominent Machine Learning (ML) algorithms to extract meaningful patterns between the composition of passengers and the corresponding energy demands in a ship. In this way, our approach is able to predict alternative energy consumption scenarios and trigger insights concerning the overall energy management in a ship. In addition, it handles the underlying uncertainty and offers highly informative visualizations of the energy consumption.

The work reported in this chapter is carried out in the context of the ECLiPSe project (http://www.eclipse-project.upatras.gr), which aims at leveraging existing technological solutions to develop an integrated energy consumption and energy saving management system for the needs of large passenger and cruise ships. A major task of the project concerns the development of efficient algorithms for the analysis and synthesis of the associated multifaceted data, which may considerably enhance the

quality of the related decision-making issues during the operation of a vessel. These algorithms may trigger recommendations about the management of energy consumption, and accordingly enable stakeholders gain energy saving insights.

The remainder of this chapter is organized as follows: Section 1.2 presents the related work aiming to justify and highlight the particularities of our approach. Section 1.3 describes the proposed approach that builds on the synergy of simulation and machine learning. Section 1.4 explains the data model and the selection of all the constants and variables applied, while Section 1.5 presents in detail the proposed system architecture. Section 1.6 presents indicative experiments and corresponding results from the application of the proposed approach and the analysis of the associated data through appropriate ML algorithms. Section 1.7 comments on the associated data analysis and synthesis issues. Finally, Section 1.8 discusses concluding remarks and Section 1.9 briefly reports on future work directions.

1.2 Background

As mentioned in the previous section, while considerable research has been conducted so far on the optimization of various energy consumption issues in buildings (being they smart or not), very limited work has been reported so far in the case of large ships. Due to this reason, the work discussed in this section concerns related approaches in (smart) buildings or parts of them (e.g. offices). As a general remark, we note that many of these approaches are based on simulation models and start utilizing ML algorithms.

A representative case of an agent-based model for office energy consumption is described in [Zhang et al., 2010]. This work elaborates the elements that are responsible for energy consumption and presents a mathematical model to explain the energy consumption inside an office. The proposed model is validated through three sets of experiments giving promising results.

Energy consumption and emission of the maritime is studied in [Zheng et al., 2019]. The authors introduce an artificial neural network model in order to explore the sailing data, aiming to predict the fuel consumption for cruise ships. Authors aim to minimize the fuel consumption, achieving the economic and environmental protection of a voyage using for optimization algorithms It is demonstrated that their method and tool can be used to plan the sailing speed of cruise ships in advance.

Adopting another perspective, a review of ML models for energy consumption and performance in buildings is presented in [Seyedzadeh et al., 2018]; the motivation of this work was the exploitation of contemporary technologies, including network communication, smart devices and sensors, towards enhancing the accuracy of prediction in the above energy management issues. On a similar research direction, a combination of mathematical statistics and neural network algorithms to solve diverse energy consumption problems is proposed in [Guzhov and Krolin, 2018]; this work analyzes the associated big data aiming to facilitate energy consumption predictions for various types of buildings.

Using a Gaussian process, the researchers in [Yuan and Nian, 2018] developed a model to predict the fuel consumption under different circumstances, running the model in different scenarios. In the introduced model, the effects of speed and trim and the impact of the wind and waves were considered and evaluated. The study indicated the accuracy and also efficiency using Gaussian process for energy consumption prediction.

Another study based on the energy consumption and gas emissions is described in [Sun et al., 2013]. The comparison has been made between inland river shipping and seagoing ships. The authors took data in calm water and real navigation conditions and calculated at the end the energy efficiency operation. The results show that the environment can affect significantly the operational energy efficiency of ships.

A comparative analysis of energy saving solutions in buildings appears in [Chebotarova et al., 2019]; the proposed tool for assessing the effectiveness of energy saving technologies implementation allows not only to evaluate individual decisions, but also to compare and rank them according to the breakeven rate for the efficiency implementation decline. A combination of Nearest Neighbors and Markov Chain algorithms for the implementation of a system that is able to support decision making about

whether to turn on or off a device in a smart home setting, thus handling the related energy management issues, is described in [Rajasekaran et al., 2017].

As argued, one should thoroughly analyze the nature of available or collectable data and the particular application, to choose the most suitable approach. In any case, it is admitted that ML algorithms may enable stakeholders gain insights from energy usage data obtained under different scenarios. For instance, the ML-based smart controller for a commercial buildings HVAC (heating, ventilation, and air conditioning) system that is described in [Javed et al., 2018] managed to reduce its energy consumption by up to 19.8%.

In [Uyanık et al., 2019]. authors use different methods of artificial intelligence to estimate the fuel a ship consumes during a trip. The authors have taken data from a commercial ship and divided them into training and data set. Using multiple linear regression, the computer has been taught to estimate data that are not known. The predictions made by ML are finally compared against real data.

Baldi [2013] aims at filling a gap in the existing scientific knowledge on the way energy in its different forms is generated, converted, and used on board of a vessel. This is done by applying energy and exergy analysis to ship energy system analysis. The results of this analysis allow improving the understanding of energy flows on board and identifying the main inefficiencies and waste flows.

A different perspective is adopted in [Kaddari et al., 2018] which elaborates the reduction of energy consumption in pumping stations. By comparing the energy consumption of a station during a 15 days period and what would the station consume in the same period after the energy audit, one may quantify the gain resulting from the use of the proposed management system. After examining the existing state of a pumping station, evaluating its energy performance and developing improvement actions, this work proposes a set of solutions improving energy consumption.

Authors in [Guohao et al., 2011] present state of ship energy consumption evaluation in China and abroad is analyzed. A mathematical modeling method of fuzzy evaluation is adopted to evaluate ship energy

consumption. Six indexes for fuzzy evaluation are set up, and the weight vectors of the index system in level one evaluation and level two evaluation are both determined through expert investigations. The energy consumption evaluation of a ship is carried out. It is indicated by analysis that fuzzy evaluation is suitable for evaluating ship energy consumption. The result is instructive for ship energy consumption evaluation.

A new method to model the ship energy flow and thus understand the dynamic energy distribution of the marine energy systems is introduced in [Guangrong et al., 2013] using the Matlab/Simscape environment, a multi-domain simulation method is employed. As reported, the proposed method can help people better monitor the ship energy flow and give valuable insights about how to efficiently operate a vessel. In a similar research line, aiming to provide a better understanding of the use of energy, of the purpose it serves, and of the efficiency of its conversion on board, an analysis of the energy system of a cruise ship operating in the Baltic Sea is provided in [Baldi et al., 2018] being based on a combination of direct measurements and computational models of the energy system of the ship, the proposed approach ensures to provide a close representation of the real behavior of the system.

1.3 Our Overall Approach

The work reported in this chapter is carried out in the context of a two-year research project, which comprises four major phases, namely (i) analysis of energy consumers in large passenger and cruise ships, (ii) development of methods to analyze and process the associated data, (iii) development of basic services for the visual representation of energy consumption, and (iv) development of an innovative platform to facilitate the related decision making process. Through these phases, the project will develop contemporary methods to gather, aggregate and analyze heterogeneous data representing both the energy consumption in diverse devices and facilities and the concentration of passengers in different areas of a ship. In addition, the project will develop a set of novel services aiming to optimize the management of energy consumption. Finally, the project will produce a set of guidelines for energy saving in a ship.

Our approach adopts the Action Research paradigm [Checkland and Holwell, 1998], which aims to contribute to the practical concerns of people in a problematic situation; it concerns the improvement of practices and strategies in the complex setting under consideration, as well as the acquisition of additional knowledge to improve the way shipping stakeholders address issues and solve problems. Building on the strengths of existing related work, as reported in the previous section, the proposed approach comprises two main phases: (i) agent-based simulation of the energy consumption in various sites of a ship, and (ii) utilization of prominent ML algorithms on the outputs of multiple simulation runs to extract meaningful insights about the relation between the passenger composition and corresponding energy demands. Through these phases, our approach is able to gather, aggregate and analyze heterogeneous data representing both the energy consumption in diverse devices and facilities and the concentration of passengers in different areas of a ship.

To fine tune our approach, a series of meetings with shipping companies were conducted; through them, we identified the types of devices and facilities that mainly affect energy consumption in the ship categories under consideration, and obtained valuable information concerning the parameters to be taken into account in energy consumption models (such as that energy supply in a ship is provided by a number of electric power generators, which – in most cases – are of different capacity and do not work in parallel). In addition, information collected concerned the layout of ship decks and its relation to the energy management issues investigated. Finally, we clarified issues related to the alternative types of passengers and how these may influence alternative energy consumption and energy saving scenarios.

1.3.1 *Agent based Simulation*

Our approach aims to enable stakeholders predict the energy needs of a ship (e.g. to recommend the appropriate number of power generators to operate each time), facilitate predictive maintenance issues (affecting the related equipment), and hopefully reduce the energy related operating costs. This approach facilitates the modeling of energy consumption,

especially for ships that do not have sophisticated energy consumption monitoring and control systems. To fulfil these aims, our agent-based simulation model takes into account the passengers' behavior and its dependencies with a ship's facilities, devices and resources.

A basic assumption of our approach is that the energy demands in many sites of a ship (such as the restaurant, the nightclub, the kindergarten etc.) depend on the number of passengers who gather at these sites at a given time, as well as their composition in terms of type (customer or crew member), age, gender etc. We consider that different age groups have different paths and habits (differences among passenger groups may even affect the speed of a moving agent). To estimate the populations gathered in these sites, we relied on the behavioral preferences that large subgroups of passengers have. For instance, we assume that young passengers prefer to spend their time at nightclub from 10pm to 3am, while elderly passengers prefer to eat dinner at a fancy restaurant. Our model may also simulate the behavior of Persons With Special Needs (PWSN); in particular, we assume that these people move at a slower pace and are in most cases accompanied by another person. Such assumptions enable us to predict the gathered populations and, accordingly, the energy demands during day and night. This approach facilitates the modeling of energy consumption, especially for ships that do not have sophisticated energy consumption monitoring and control systems.

In addition, according to our approach, the passengers' behavior is being considered and modelled through three basic scenarios corresponding to the ship (i) being moved during the day, (ii) being moved during the night, and (iii) being anchored at a destination or port. In the above scenarios, we assume different behaviors from passengers, which may result to different energy demands. Finally, to accommodate the spatial particularities of each ship, our approach pays much attention to the layout of each deck. These layouts provide us with the spatial data that are needed to calculate the movement of passengers inside the ship. AnyLogic offers a user-friendly import of sectional plans (views), thus enabling the production of a more realistic model of the distribution of ship passengers, facilities and devices. Taking into account what our models predict in terms of energy needs, we suggest different policies of energy management, aiming to reduce energy consumption.

1.3.2 *Machine Learning Algorithms*

Machine Learning (ML) is an application of Artificial Intelligence (AI) that enables information systems automatically learn and improve from past data, without being explicitly programmed. ML includes diverse approaches such as supervised learning, unsupervised learning, and reinforcement learning.

Having thoroughly assessed the palette of broadly used ML algorithms for the needs of our approach, we decided to utilize two classification algorithms, namely the Decision Trees (DT) and the K-Nearest Neighbors (K-NN) algorithms. This is due to the fact that these algorithms provide high interpretability of their results, they have low computational cost, and they fit well to our data structure.

Decision Trees is one of the simplest and widely used classifiers in the field of Data Mining. They constitute a non-parametric supervised learning method, aiming to create a model that predicts the value of a target variable by learning simple decision rules inferred from the data features. DT demonstrates excellent applicability in datasets with either categorical or continuous variables. In addition, it requires little data preparation and it is able to process large amounts of data [Rokach and Maimon, 2008].

K-NN is a simple supervised ML algorithm that can be used for both classification and regression problems, and has been extensively applied in diverse disciplines, such as Economics and Health [Cunningham & Delany, 2007]. It relies on labeled input data to learn a function that produces an appropriate output when given new unlabeled data. In most cases, K-NN yields competitive results and has significant advantages over other data mining methods. It differs from other classifiers in that it does not build a generic classification model; instead, whenever a new record is being inserted in the system, it tries to find similar records (nearest neighbors) from past data stored in its memory and assigns it the value of the dependent variable that its neighbors have.

1.4 Data Model

One of the main variables to be taken in to account concerns the passengers on board, as well as their composition in terms of type (customer or crew member), age, gender etc. As mentioned above, different age groups have different paths and habits; for example, elderly passengers go to sleep earlier than the kids, so the corridors have to have enough light to satisfy both groups. The difference between the age groups affects also the speed that an agent can have, which it will be also different from a person with special needs. Another important variable considered is the ship layout (at the deck level). These layouts provide information about the detailed coordinates of all ship locations, including passenger cabins and facilities of the ship. Each energy consuming device is also a variable in our model.

1.5 System Architecture

Through user-friendly interfaces, our approach enables stakeholders to build and run alternative energy consumption scenarios. These scenarios are populated with data that are either given by the user or already stored in the application's repository. The execution of scenarios is through the AnyLogic simulation engine, which results to the creation of illustrative reports and associated energy saving directions ('recipes'). A middleware component establishes the connection between the application's back-end and front-end, while also enabling the interoperability of the proposed application with external services.
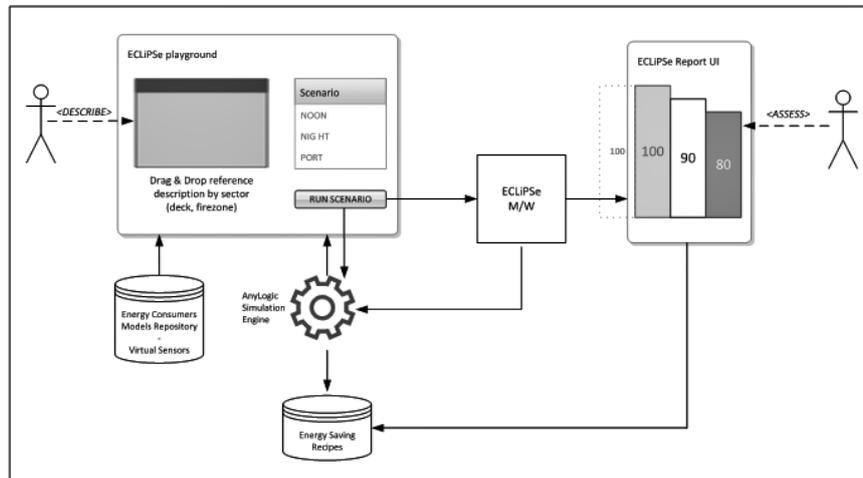
Fig. 1.1. The architecture of the proposed application.

Figure 1.1 sketches the components and overall architecture of the proposed application. As shown, the four main components (microservices) of the proposed application are:

- The service that describes the scenario and the specifications of the desired energy modeling and analysis. Initially, this service specifies all the necessary specifications of the AnyLogic simulation tool models. In a future version, this service will include data from smart energy consumption meters or actual passenger position / movement.
- The basic simulation service of energy consumption scenarios. This service is responsible for the simulation of various energy consumption scenarios in order to support managers of the passenger ship draw conclusions about energy consumption optimization.
- The results display service, which provides simulation results in various formats including raw data reports, comparison charts, etc.
- The data analysis service, which relies on ML algorithms and tries to detect trends and behaviors regarding energy consumption and possible ways to optimize it.

1.6 Experiments

This section illustrates a particular set of experiments carried out to assess the applicability and potential of our application for a specific vessel. In particular, we elaborate energy demands that are associated with four popular facilities of a ship, namely (i) the night club, (ii) the kindergarten, (iii) the casino, and (iv) the restaurant. For the case under consideration, we consider and import in the simulation software the original deck layouts, where all ship facilities and passenger cabins are mapped. Moreover, we assume a total population of 3100 passengers onboard, belonging to four distinct age groups (i.e. 1-14, 15-34, 35-54, ≥55 years old). Table 1.1 summarizes sample data concerning the populations of each age group in the facilities considered. For each individual group of passengers, we create a simple linear behavioral model in which each individual group remains in a specific facility for some time. We do this for every group of passengers and every time period to create a comprehensive routine for all passengers throughout the day. In this way, we are able to simulate diverse scenarios, which may be easily aggregated to create an illustrative energy consumption map for the whole vessel.

Table 1.1. Distribution of age groups in various ship facilities.

Ship's Cite	Age Group	1-14	15-34	35-54	≥55
Nightclub	Percentage	0%	60%	30%	**10%**
	Population	0	300	150	**50**
Kindergarten	Percentage	35%	10%	55%	**0%**
	Population	53	15	82	**0**
Restaurant	Percentage	12%	8%	35%	**45%**
	Population	46	30	134	**172**
Casino	Percentage	0%	0%	35%	**65%**
	Population	**0**	**0**	**112**	**208**

1.6.1 *Nightclub*

For the case elaborated in this chapter, we generated random samples of 500 passengers, assuming that the percentage of passengers visiting this facility is between 15% and 17%. This facility operates from 11pm to 5am. The conditional probability of someone visiting the night club is shown in Table 1.1. We also set the time spent there (from passengers of all age groups) to follow a triangular distribution with a lower limit equal to 50 minutes, mode equal to 95 minutes, and upper limit equal to 110 minutes. Finally, we imported the layout of a specific deck, where detailed spatial data about the cabins and the possible pathways leading to the night club area are described. By running the corresponding simulations, we are able to visualize the possible concentration of passengers during the night at this area of the ship (see Figure 1.2).

Consequently, by estimating the energy requirements of the night club with respect to the number of passengers hosted, we can calculate the possible energy needs for the particular time period and facility (see Figure 1.3). Such estimations can be used for future predictions of energy consumption in cases where passengers are distributed in a similar way. Furthermore, the derived data can be statistically analyzed to reveal the data patterns and mechanisms that may cause the particular energy demands
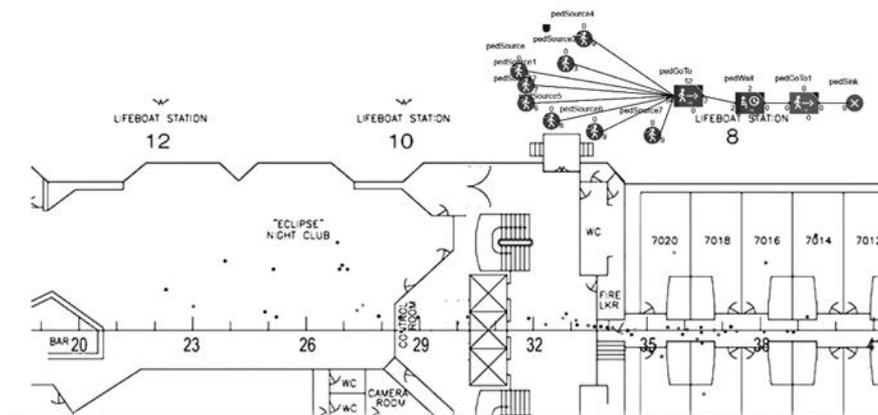

Fig. 1.2. Energy demands corresponding to passengers' concentration in the nightclub.
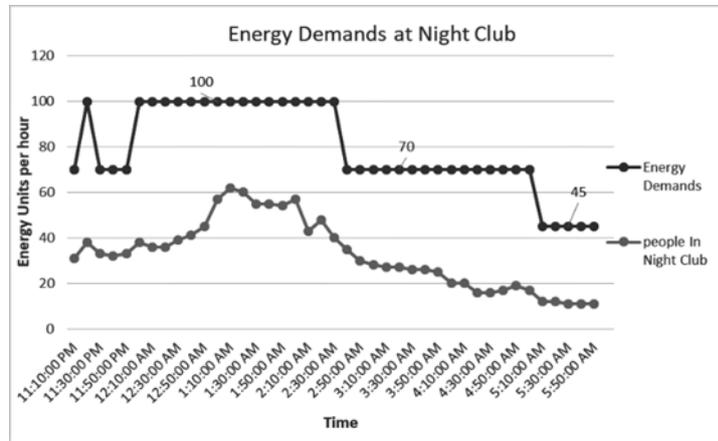
Fig. 1.3. An instance of a simulated energy consumption scenario in the nightclub.

1.6.2 *Kindergarten*

For this facility (see Figure 1.4), we considered that the passengers who visit it are mainly children (1-14 years old) and their parents (who may belong into the age groups of 15-34 and 35-54 years old). The opening hours of this facility are from 11am to 2pm. We assumed that the kindergarten is not the only choice that the above groups have for entertainment purposes. Also, compared to other areas on the ship, the kindergarten is not large enough to accommodate all parents with their children.

We have therefore assumed that the proportion of passengers visiting it daily ranges from 4% to 5.5%, i.e. from 120 up to 176 persons. The time people spend while visiting this facility is described by a triangular distribution with a minimum time of 50 minutes, a maximum time of 110 minutes, and a dominant value of 80 minutes. The experiments carried out gave the concentration of passengers shown in Figure 1.5.
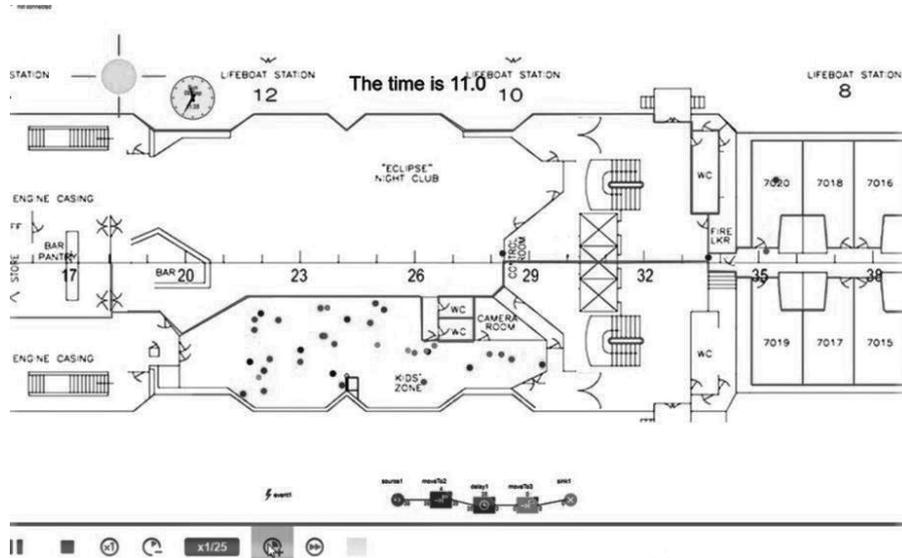
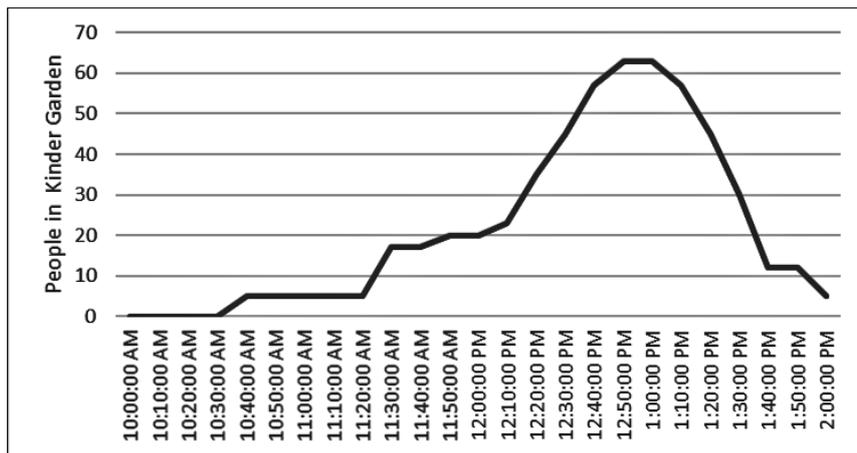Fig. 1.4. An instance of a simulated energy consumption scenario in the kindergarten.

Fig. 1.5. Passengers' concentration in the kindergarten.

1.6.3 *Casino*

The samples of passengers used in the particular set of experiments concerned 320 people (i.e. 10% of average passengers' population). We assumed that this facility operates from 7pm to 7am and mainly attracts passengers that are older than 35 years old (65% of them belonging to the ≥55 age group and the remaining 35% to the 35-54 age group). Moreover, passengers that visit the casino are divided into two categories, those who choose to waste their time exclusively in the casino during the night (20%) and those who visit the casino for a certain time period (they may leave and re-enter the casino during the night). The first category concerns the 20% of the casino visitors (their stay follows a triangular distribution with a minimum time of 250 minutes, a maximum of 300 minutes and a dominant value of 270 minutes). Similarly, for the rest 80% of casino visitors we considered that their time spent follows a triangular distribution with a minimum time of 20 minutes, a maximum time of 80 minutes and a dominant value of 35 minutes).

As illustrated in Figure 1.7, there is a two peaks distribution of passengers' concentration. This kind of distribution is called bimodal distribution because of the existence of two distinct modes. In our approach, the bimodal distribution is the aftereffect of our assumption that passengers visiting Casino can be classified into two different subgroups.

Fig. 1.6. An instance of a simulated energy consumption scenario in the casino area.

Fig. 1.7. Passengers' concentration in the casino area.

1.6.4 *Restaurant*

We considered one of the available ship restaurants (offering an "à la carte" menu, thus not being an economic one), operating from 7pm to 11pm. This facility concerns all passengers, regardless of age group. We assumed that 10%-12% of passengers (320-380 people) choose this particular restaurant; their stay is described by a triangular distribution with a minimum time of 75 minutes, a maximum time of 150 minutes and a dominant value of 120 minutes.
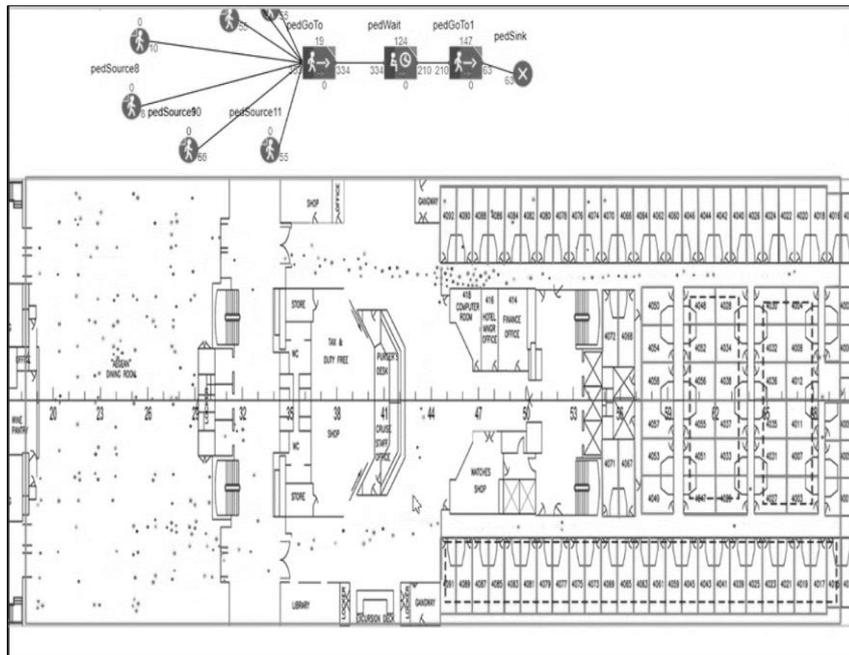

Fig. 1.8. An instance of a simulated energy consumption scenario in the restaurant area.

Figure 1.8 depicts an over-concentration of passengers at a main ship's corridor leading to the particular restaurant. This phenomenon can be identified as a problem of bad operation scheduling in one of the ship's cites that could possibly cause inconveniences and/or delays in passengers' service. Such problems can be diagnosed by running the appropriate simulation models under the right assumptions.
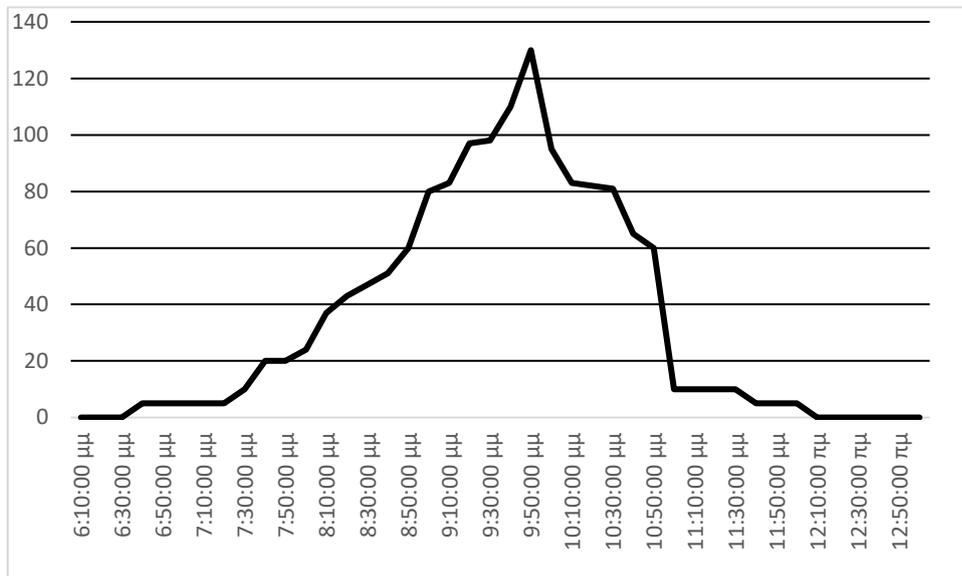
Fig. 1.9. Passengers' concentration in the restaurant area.

1.7   Data Analysis and Synthesis

The experiments described above demonstrate diverse features and options offered by the proposed simulation model. To predict energy consumption in large passenger and cruise ships, our approach aggregates results obtained from each particular facility of a ship and produces a corresponding time series diagram, in which the dependent variable is the energy consumption measured in energy units per hour and the time interval is 10 minutes. Figure 1.10 illustrates the overall energy demands with regards to the estimated gathering of passengers in the facilities discussed in the previous section throughout the day.

Obviously, our experiments have not considered the entirety of facilities and energy consumers available on a ship (such as air condition, lighting, heating etc.); however, all of them can be easily aggregated to

our model and thus provide a detailed mapping of the overall energy consumption.

Building on the proposed agent-based simulation model that facilitates the creation of alternative energy consumption scenarios, we can produce realistic data that can be further elaborated by prominent machine learning algorithms to provide meaningful insights for managing diverse energy consumption patterns [Deist et al., 2018]. Parameters taken into account by the proposed machine learning algorithms also include the number of ship generators (categorical variable), the alternative age groups and their populations (as defined for each ship), and the time slots considered each time (the ones adopted in our approach are shown in Table 1.2).
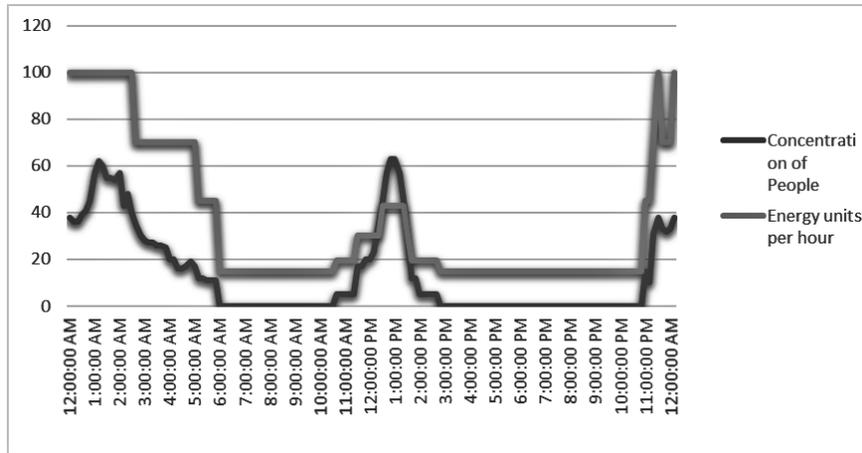

Fig. 1.10. Cumulative concentration of passengers in four major ship's facilities and corresponding energy demand.

Table 1.2. Time slots considered in our approach.

Time interval	Time slot
7:00am – 11:59am	Morning
12:00pm – 4:59pm	Midday
5:00pm – 9:59pm	Evening
10:00pm – 6:59am	Night

Table 1.3. Sample of our DataSet.

Composit ion ID	Age Groups				PWSN	Time slot	Number of gen. in simulta- neous operation
	1-14	15-34	35-54	≥55			
1	290	535	945	1432	97	Morn.	3
						Mid.	2
						Even.	4
						Night	3
2	200	750	1200	1100	75	Morn.	2
						Mid.	3
						Even.	4
						Night	4
3	175	700	1150	1150	20	Morn.	2
						Mid.	3
						Even.	4
						Night	4
4	48	885	1890	550	100	Morn.	1
						Mid.	3
						Even.	4
						Night	3

In our experiments, we generated a large dataset of 919 different passenger compositions for each time slot. A small sample of this dataset, concerning only four of these compositions for the time slots defined, is presented in Table 1.3 (the number of generators that operate for each data combination is calculated upon the definition of a set of energy unit intervals and their association with the energy produced by the simultaneous operation of a certain number of generators). A big part of this dataset (70%) was used as the training set of the two ML algorithms incorporated in our approach. Through the utilization of these algorithms, one may predict the required number of generators per time slot for a specific passenger composition.

Focusing on the 'morning' time slot, Figure 1.12 illustrates the output of the Decision Tree algorithm, which classifies alternative passenger

compositions into different numbers of power generators required. As it can be observed, the energy consumption of the ship in this time slot is being affected by (i.e. positively correlated to) the ratio of passengers that are older than 55 to those that are younger than 35 years old. The interpretation of this may be that older people use to be more active in the morning (compared to young populations). Results shown in Figure 1.11 provide additional evidence in favor of the above insight; as depicted, the correlation between the number of generators being used in the morning and the number of elderly passengers is positive.
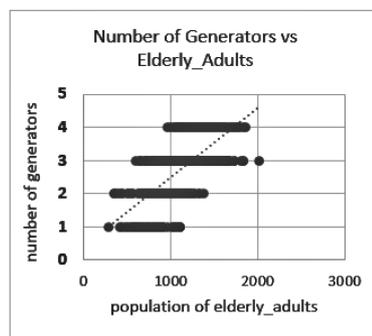

Fig. 1.11. Scatter plot - number of generators vs population of elderly passengers.
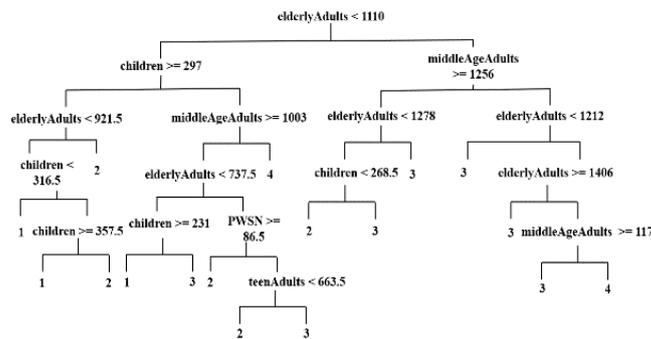

Fig. 1.12. Decision Tree classification ('children', 'teenAdults', 'middleAgeAdults' and 'elderlyAdults' correspond to the 1-14, 15-34, 35-54 and >=55 age groups, respectively).

For the abovementioned time slot, we also applied the K-NN algorithm. The confusion matrix produced (this matrix is actually a technique for summarizing the performance of a classification algorithm) showed us limited reliability. In particular, K-NN performed very well (with more than 95% accuracy) when classifying compositions of passengers that were associated with the operation of one or four generators, while this was not the case for compositions associated with the operation of two or three generators (in these cases, the accuracy was about 45% and 55%, respectively).

Table 1.4 summarizes a small set of predictions produced by the K-NN algorithm for the cases of one or four generators operating simultaneously. It is noted that for these cases K-NN produces very similar results to those obtained by the Decision Tree, i.e. the energy needs are positively correlated to the ratio of passengers that are older than 55 to those that are younger than 35 years old.

Table 1.4. Predictions produced by K-NN algorithm.

Age Groups				PWSN	Number of generators in simultaneous operation
1-14	15-34	35-54	≥55		
100	755	1100	1300	75	4
270	668	916	1570	43	4
174	968	865	1021	40	4
243	755	1412	656	41	1
328	686	1450	678	82	1
410	995	1425	780	10	1

1.8 Conclusions

The application described in this chapter advances the way stakeholders of large passenger and cruise ships deal with energy consumption issues, by building on a comprehensive and informative simulation model that

facilitates the creation and assessment of alternative energy saving scenarios. We argue that our overall approach suits particularly to ships that are not equipped with state-of-the-art (smart) energy management sensors and devices. To accommodate this situation, our approach produces realistic data that can be analyzed and give insights for the mechanisms of energy consumption.

The prediction of energy consumption in large passenger and cruise ships is certainly a hard problem. This is mainly due to the need to simultaneously consider the interaction between multiple parameters and agent behaviors. To deal with this problem, the proposed approach blends the process-centric character of a simulation model and the data-centric character of ML algorithms.

By building on a comprehensive and informative agent-based simulation model, our approach facilitates the generation and assessment of alternative energy consumption scenarios that incorporate vast amounts of realistic data under various conditions. Moreover, it advocates the use of prominent machine learning algorithms to aid the finding, understanding and interpretation of patterns that are implicit in this data, ultimately aiming to provide meaningful insights for shaping energy saving solutions in a ship.

1.9 Future Work

The proposed approach promotes the way cruise ships deal with energy consumption. It provides the management of the cruise ship with a lot of information that can facilitate the reduction of energy waste. One step towards this solution should be the production of realistic data that can be analyzed to trigger insights about the mechanisms of energy consumption. The projected energy requirements should formulate a set of management rules for dealing with energy consumption at the energy saving stage. In addition, the production of realistic data can lead us to produce more sophisticated results by applying machine learning algorithms and finally being able to promote the ideal energy management policy regarding passenger composition.

Our future work includes the comparison of the outputs of the proposed approach with real data. As far as the outcomes produced by the agent-based simulation model are consistent with real data, our machine learning algorithms will be better trained, which will in turn enhance the accuracy of the associated energy consumption predictions. Such reinforcement learning activities consist one of our future work directions. Other directions include the investigation of alternative modes to combine simulation and machine learning. Specifically, we plan to consider the application of ML algorithms prior to and within the simulation. In the former case, we will need real data to develop rules and heuristics that our agent-based simulation model can then employ. In the latter, we may reuse previously trained ML-based models or train the ML models as the simulation is taking place.

1.10   References and Citations

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