Chapter 5

Agent Based Simulation Model for Energy Saving in Large Passenger and Cruise Ships

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Abstract

The prediction of energy consumption in large passenger and cruise ships
is certainly a complex and challenging issue. Aiming to address it, this
chapter reports on the development of a novel approach that builds on a
sophisticated agent-based simulation model. The proposed approach takes
into account diverse parameters such as the size, type, and behavior of
the different categories of passengers on-board, the energy-consuming fa-
cilities and devices of a ship, spatial data concerning the layout of a ship's
decks, as well as alternative ship operation modes. Output obtained from
multiple simulation runs is then exploited by prominent Machine Learning
algorithms to extract meaningful data patterns concerning the composition

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of passengers and the corresponding energy demands. In this way, the proposed approach can predict alternative energy consumption scenarios and trigger meaningful insights concerning the overall energy management in a ship.

5.1. Introduction

Undoubtedly, energy saving is of paramount importance in the shipping industry, as far as both the protection of the environment and the reduction of the associated operating costs are concerned. In this direction, the International Maritime Organization (IMO) 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 [1].

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 sulfur than several million cars, more NO_2 gas than all the traffic passing through a medium-sized town and more particulate emissions than thousands of buses in London [2]. While the cruise ship industry starts taking its first steps toward an emission-free cruise, cruise travels are among the most carbon-intensive ships in the tourism industry; the contribution of the cruise industry to global CO_2 emissions was estimated to be 19.3 Mtons annually in 2010 [3].

To the best of our knowledge, while energy-saving solutions have been thoroughly investigated in the case of (smart) buildings, very limited research [4] [5] has been conducted so far for the above-mentioned 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 on-board, 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 cruising during day or night, or being stopped at a port; (iii) different pas-

senger groups in terms of their size and behavior, by considering that the energy consumption of many devices or facilities (e.g., restaurant, air conditioner, etc.) depends on the number of passengers in them or nearby. 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 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 multi-faceted 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 to gain energy saving insights.

The remainder of this chapter is organized as follows: Section 5.2 presents the related work aiming to justify and highlight the particularities of our approach. Section 5.3 describes the proposed approach that builds on the synergy of simulation and ML. Section 5.4 explains the data model and the selection of all the constants and variables applied, while Section 5.5 presents in detail the proposed system architecture. Section 5.6 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 5.7 comments on the associated data analysis and synthesis issues. Finally, Section 5.8 discusses concluding remarks and Section 5.9 briefly reports on future work directions.

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5.2. 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 (whether they are 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 con-
sumption is described in [6]. 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 industry is studied
in [7]. 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 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 con-
sumption and performance in buildings is presented in [8]; the motivation
of this work was the exploitation of contemporary technologies, including
network communication, smart devices, and sensors, toward enhancing the
accuracy of prediction in the above energy management issues. In a similar
research direction, a combination of mathematical statistics and neural net-
work algorithms to solve diverse energy consumption problems is proposed
in [9]; 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 [10] 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 evalu-
ated. The study indicated the accuracy and also the efficiency of using the
Gaussian process for energy consumption prediction.

Another study based on energy consumption and gas emissions is de-
scribed in [11]. A comparison has been made between inland river shipping

and seagoing ships. The authors took data in calm water and real naviga-
tion conditions and calculated at the end the energy efficiency operation.
The results show that the environment can affect significantly the opera-
tional energy efficiency of ships.

A comparative analysis of energy-saving solutions in buildings appears
in [12]; the proposed tool for assessing the effectiveness of energy-saving
technologies implementation allows not only to evaluate individual deci-
sions, but also to compare and rank them according to the breakeven rate
for the efficient implementation decline. A combination of Nearest Neigh-
bors and Markov Chain algorithms is described in [13] for the implementa-
tion 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.

As argued, one should thoroughly analyze the nature of available or
collectible data and the particular application, to choose the most suitable
approach. In any case, ML algorithms may enable stakeholders to gain
insights from energy usage data obtained under different scenarios. For
instance, the ML-based smart controller for a commercial building's HVAC
(heating, ventilation, and air conditioning) system that is described in [14]
managed to reduce its energy consumption by up to 19.8%. In [15], 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.

The author in [16] aims at filling a gap in the existing scientific knowl-
edge on the way energy in its different forms is generated, converted, and
used on-board a vessel. This is done by applying energy and exergy analysis
to ship energy system analysis. The results of this analysis allow improv-
ing the understanding of energy flows on-board and identifying the main
inefficiencies and waste flows.

A different perspective is adopted in [17] which elaborates the reduction
of energy consumption in pumping stations. By comparing the energy con-
sumption 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

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set of solutions to improving energy consumption.

The authors in [18] 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 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 [19] using the MATLAB/Simscape environment, a multi-domain simulation method is employed. As reported, the proposed method can help people better monitor the ship's 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, the purpose it serves, and 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 [20] 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.

5.3. Overall Approach

The work reported in this chapter is carried out in the context of a two-year research project, which comprises of 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 [21], 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, the 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.

5.3.1. *Agent-Based Simulation*

Our approach aims to enable stakeholders to 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 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 fulfill 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, nightclub, the kids' daycare,

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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 of large sub-groups of passengers. For instance, we assume that young passengers prefer to spend their time at a nightclub from 10 pm to 3 am, 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 considered and modeled 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 in 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 is 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.

5.3.2. *Machine Learning Algorithms*

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

gorithms, 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,have low computational cost, and fit well into our data structure.

DT is one of the simplest and widely used classifiers in the field of data mining. It constitutes 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 data sets with either categorical or continuous variables. In addition, it requires little data preparation and it is able to process large amounts of data [22].

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 [23]. 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 into 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.

5.4. Data Model

One of the main variables to be taken into 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 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.
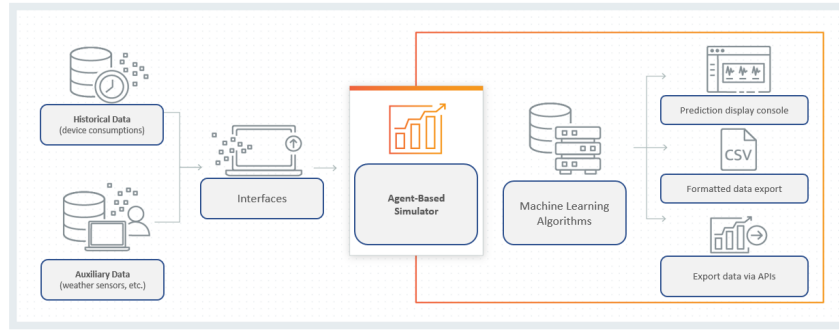
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Fig. 5.1.   Architecture of the proposed application

5.5. System Architecture

Through user-friendly interfaces, our approach enables stakeholders to build
and run alternative energy consumption scenarios. These scenarios are pop-
ulated 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 in 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.

Figure 5.1 sketches the components and overall architecture of the pro-
posed 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 simula-
  tion tool models. In a future version, this service will include data
  from smart energy consumption meters or actual passenger posi-
  tion/movement.
- The basic simulation service of energy consumption scenarios
  ,which service's is responsible for the simulation of various energy
  consumption scenarios in order to support managers of the passen-
  ger ship draw conclusions about energy consumption optimization.
- The results display service, which provides simulation results in

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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.

5.6. 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 on energy demands that are associated with four
popular facilities of a ship, namely, the (i) night-club, (ii) kids'daycare, (iii)
casino, and (iv) 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 on-board, belonging to four distinct
age groups (i.e., 1-14, 15-34, 35-54, $\geq$55 years old). Table 5.1 summarizes
sample data concerning the populations of each age group in the facilities
considered. For each group of passengers, we create a simple linear be-
havioral model in which each group remains in a specific facility for some
time. We do this for every group of passengers and every period to create a
comprehensive routine for all passengers throughout the day. In this way,
we can simulate diverse scenarios, which may be easily aggregated to create
an illustrative energy consumption map for the whole vessel.

Table 5.1.   Distribution of age groups in various ship facilities

Ship's Facility	Age Group	1-14	15-34	35-54	$\geq$55
Nightclub	Percentage	0	60	30	10
	Population	0	300	150	50
Kids'daycare	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

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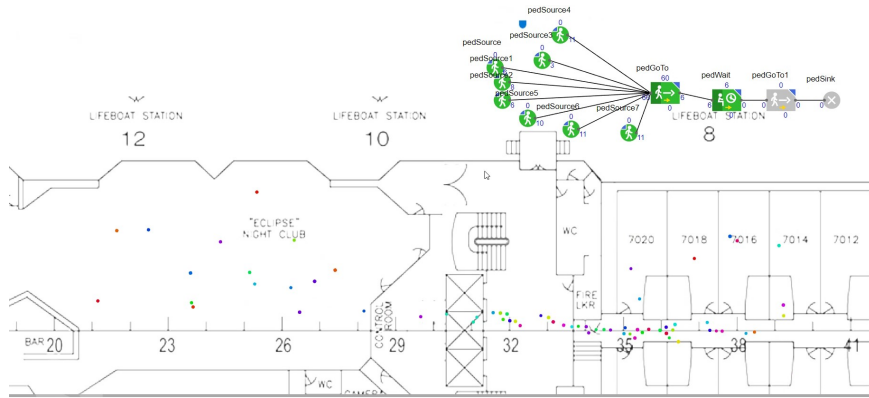

Fig. 5.2.   Energy demands corresponding to passenger concentration in the nightclub

5.6.1.   *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 11 pm to 5 am. The conditional probability of someone visiting the night club is shown in Table 5.1. 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 5.2).

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 5.3). 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.
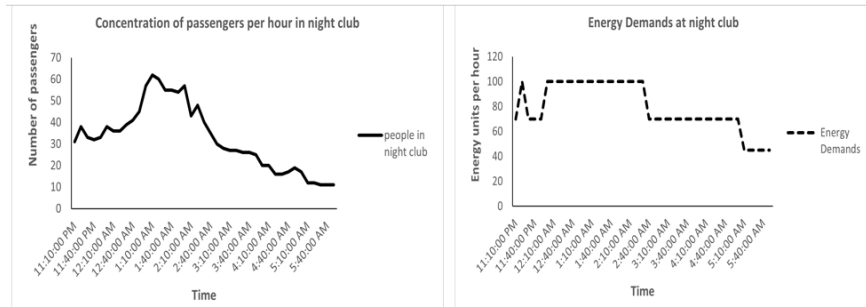
Fig. 5.3.   An instance of a simulated energy consumption scenario in the nightclub
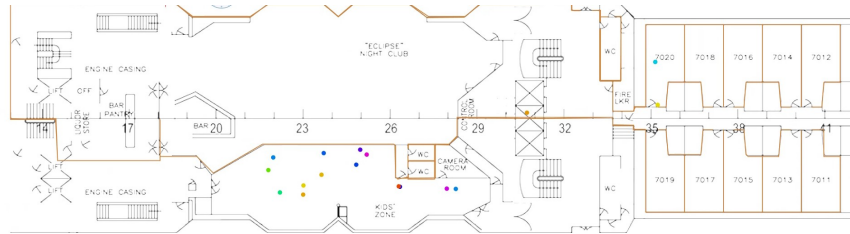

Fig. 5.4.   An instance of a simulated energy consumption scenario in the kids'daycare

5.6.2. *Kids'Daycare*

For this facility (see Figure 5.4), 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 11 am to 2 pm. We assumed that the daycare is not the only choice that the above groups have for entertainment purposes. Also, compared to other areas on the ship, the daycare 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 of 50 minutes, maximum of 110 minutes, and dominant value of 80 minutes. The experiments carried out gave the concentration of passengers as shown in Figure 5.5.
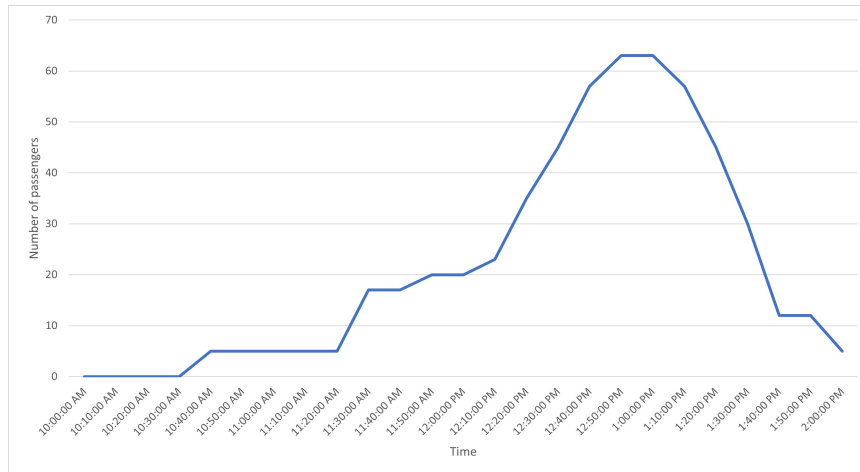
Fig. 5.5.   Passenger concentration in the kids'daycare

5.6.3. *Casino*

The samples of passengers used in the particular set of experiments concerned 320 people (i.e., 10% of average passenger population). We assumed that this facility operates from 7 pm to 7 am 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 spend 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 20% of the casino visitors (their stay follows a triangular distribution with a minimum of 250 minutes, maximum of 300 minutes, and 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 of 20 minutes, maximum of 80 minutes, and dominant value of 35 minutes).

As illustrated in Figure 5.7, there is a two-peak distribution of passenger 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 after-effect of our assumption that passengers visiting the casino can be classified into two different sub-groups.
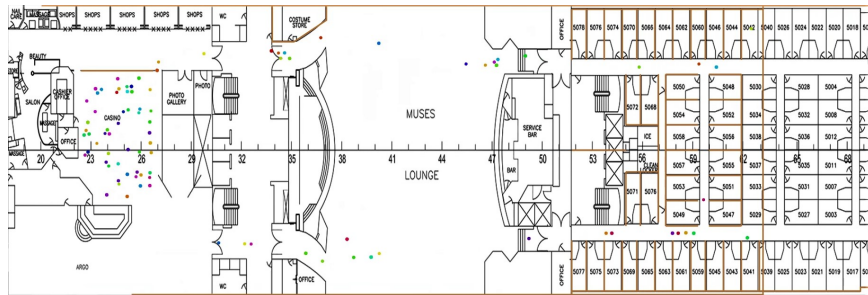
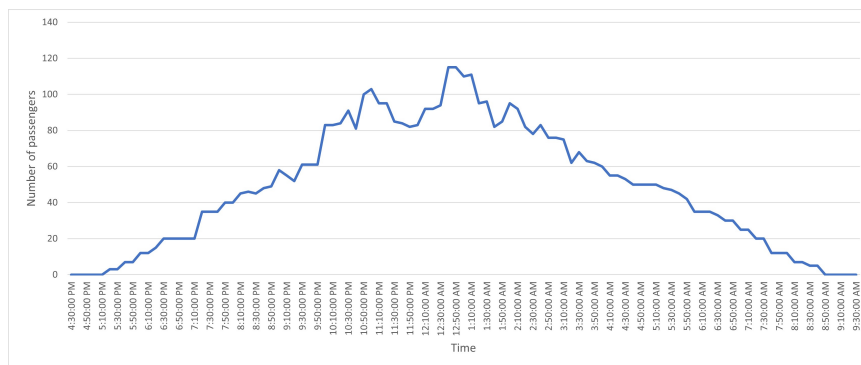Fig. 5.6.   An instance of a simulated energy consumption scenario in the casino

Fig. 5.7.   Passenger concentration in the casino

5.6.4. *Restaurant*

We considered one of the available ship restaurants (offering an "à la carte" menu, thus not being an economic one), operating from 7 pm to 11 pm. 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 of 75 minutes, maximum of 150 minutes, and dominant value of 120 minutes.

Figure 5.9 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.

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Fig. 5.8.   An instance of a simulated energy consumption scenario in the restaurant

Fig. 5.9.   Passenger concentration in the restaurant

Figure 5.9 depicts passenger concentration in the restaurant area.

5.7. 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 **??** illustrates the overall energy demands with regards to the estimated gathering of passengers in the facilities discussed in the pre-
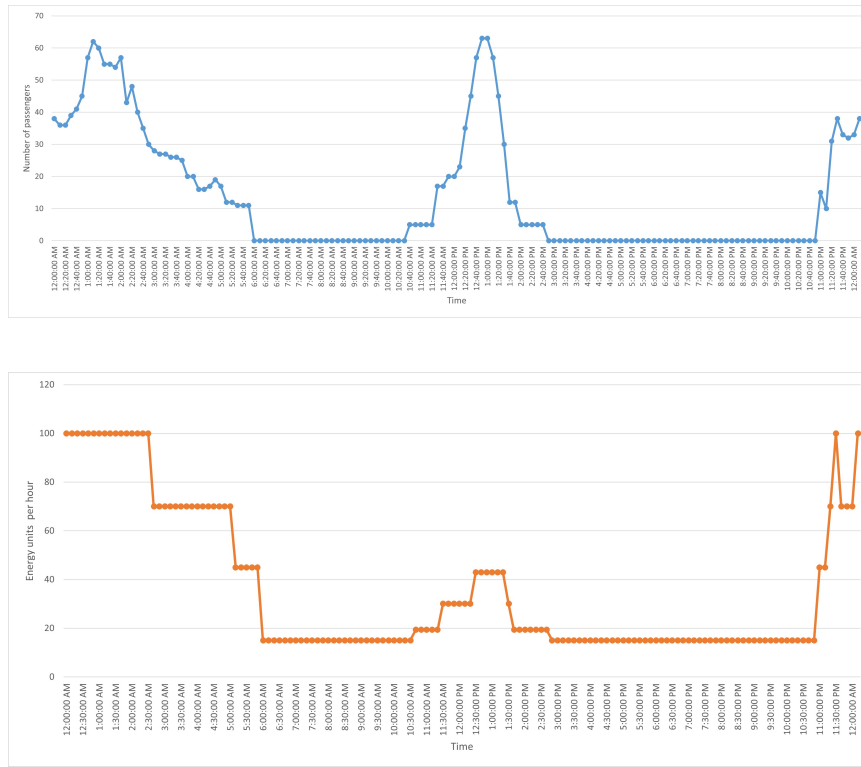
Fig. 5.10.   Cumulative concentration of passengers in four major ship facilities and corresponding energy demand

vious section throughout the day.   Obviously, our experiments have not considered the entirety of facilities and energy consumers available on a ship (such as air conditioning, 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 ML algorithms to provide meaningful insights for managing diverse energy consumption patterns [24]. Parameters taken into account by the proposed ML algorithms also include the number of ship generators (categorical variable), alternative age groups and their populations (as defined for each ship), and time slots considered each time (the ones adopted in our approach are shown in

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Table 5.2).

Table 5.2.   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

In our experiments, we generated a large data set of 919 different pas-
senger compositions for each time slot. A small sample of this data set,
concerning only four of these compositions for the time slots defined, is
presented in Table 5.3 (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 simultane-
ous operation of a certain number of generators). A big part of this data
set (70%) was used as the training set of the two ML algorithms incorpo-
rated 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 5.11 illustrates the output
of the Decision Tree algorithm, which classifies alternative passenger com-
positions into different numbers of power generators required. As it can be
observed, the energy consumption of the ship in this time slot is 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 are more active in the morning (compared to younger
populations). Results shown in Figure 5.12 provide additional evidence in
favor of the above insight; as depicted, the correlation between the number
of generators used in the morning and the number of elderly passengers is
positive.

For the above-mentioned time slot, we also applied the K-NN algorithm.
The confusion matrix produced (this matrix is actually a technique for sum-
marizing 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

Table 5.3.   Sample of our data set.

Composition ID	Age Group				PWSN*	Time Slot	Number of Generators in Simultaneous 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

*PWSN : people with special needs.

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 5.4 summarizes a small set of predictions produced by the K-NN algorithm for the cases of one of 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 who are older than 55 to those who are younger than 35 years old.

Table 5.4.   Predictions produced by K-NN algorithm

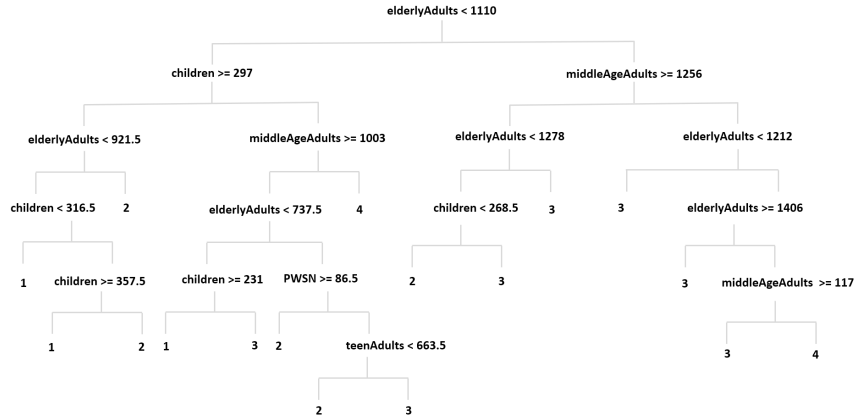| Age Group				PWSN	Number of Generators in Simultaneous Operation
1-14	15-34	35-54	≥55		
100	755	1100	1300	75	4
270	668	916	1570	43	4
174	968	865	1021	40	4
243	755	1412	656	41	1
328	686	1450	678	82	1
410	995	1425	780	10	1

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Fig. 5.11.   Decision Tree classification ('children', 'teenAdults', 'middleAgeAdults' and 'elderlyAdults' correspond to the 1-14, 15-34, 35-54 and $\geq$55 age groups, respectively)
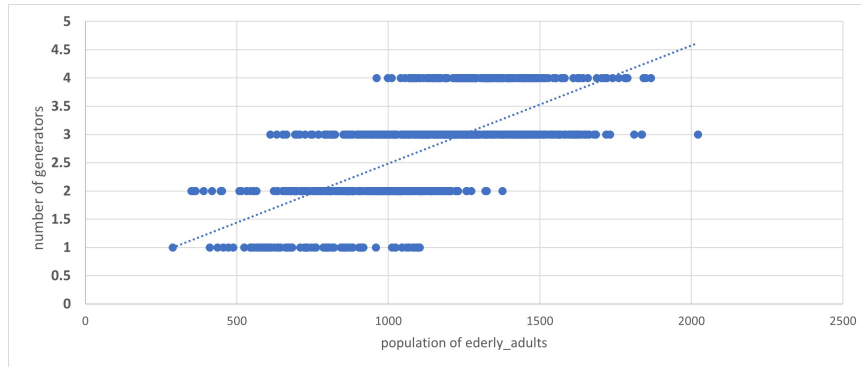

Fig. 5.12.   Scatter plot of the number of generators vs. the population of elderly passengers

5.8. Conclusion

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 ships that are not equipped with state-of-the-art (smart) energy management sensors and

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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 ML 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.

5.9. Future Work

The proposed approach in this chapter 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 toward 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 ML 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 ML algorithms will be better trained, which will in turn enhance the accuracy of the associated energy consumption predictions. Such reinforcement learning activities consist of one of our future work directions. Other directions include the investigation of alternative modes to combine simulation and ML. 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

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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.

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