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Energy–Economy Coupled Simulation Approach and Simulator Based on Individual-Based Model

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Abstract: An integrated energy system, referred to specifically as a heterogeneous energy system that combines cooling, heating, power, etc., is a dynamic system containing continuous as well as discrete behaviors on both technical and economic levels. Currently, the comprehensive utilization of multiple forms of energy and the implementation of the energy market have made the simulation of such a system very complicated, which is reflected in two aspects. First, the simulation model becomes complex and varied. Second, the time-varying characteristics of the models are quite diverse. Therefore, a standard and normative modeling and simulation method is urgently needed. This work aims to obtain a compatible modeling and simulation method for the energy economy coupling system. The individual-based model is widely used to describe organisms in an ecology system that are similar to the energy–economy coupled system. Inspired by this, a general simulation approach based on the individual-based model is proposed in this paper to overcome these existing problems. The standard formal expression model is built, then its structure and elements explained in detail, and multi-scale time simulation supported to model and simulate an integrated energy system that is coupled with markets. In addition, a simulator is designed and implemented based on multi-agent framework and model-view-controller architecture. Finally, a simulation case of a conceived scenario was designed and executed, and the results analysis proved the validity and versatility of the proposed approach. The proposed method has the advantages of model standardization, multi-scale time compatibility, distributed simulation capability, and privacy protection. These advantages support and strengthen each other. Through these studies, a systematic approach was formed that could improve the standardization of modeling and simulation in the energy–economy research area.

Keywords: energy–economy coupled system; individual-based model; modeling and simulation; multi-scale time

1. Introduction

Owing to the graded and complementary use of energy, an integrated energy system (IES) has considerable advantages as it enables more efficient use of energy and is advocated in many countries and regions. At the same time, market-based competitive transactions are being implemented with greater coverage in several energy sectors, which cause the study of physical energy systems and financial market transactions to be often intertwined [1]. The research objects of this topic include not only energy devices with different physical properties and members with economic decision-making properties, but also bidirectional influences between the two. Therefore, such a system is also called the energy–economy coupled system (EECS). Among methods used to research the EECS, modeling and simulation (M&S) plays a very important role in energy planning programming, policy making, and dynamic analysis. The core technology for an EECS simulation exists in two aspects: system level

specification and model specification formalism. The former refers to the operating principle of the simulation system, while the latter declares the structure and elements of the model.

Currently, in the fields of energy and economy research, both have their own simulation methods and scope, according to the characteristics of the study object concerned. For example, in power system research, dynamic simulations such as electromagnetic and electromechanical transient simulation programs based on different numerical calculation methods are used. Regarding a multi-energy system, several energy modeling and planning systems were built based on GAMS (the General Algebraic Modeling System), such as TIMES [2] and its original version MARKAL [3]. For an overview, the reader is referred to [4], in which a detailed introduction to 68 energy tools is given. Similarly, 24 different energy optimizers and simulators are summarized in [5], adopting multiple evaluation criteria, such as time and spatial resolution, an analytical approach, and a programming environment. Economic systems also feature a variety of simulation methods, such as agent-based simulation [6,7] and system dynamics simulation [8]. Among numerous modeling and simulation approaches, agent-based simulation is popular for its distributed ideology, which is suited to a multi-component and non-centralized coordination system. In multiple research areas, including the brain, immune system, ecosystems, societies, and financial markets, an agent-based approach has been widely applied [9]. For example, ASPEN (an agent-based simulation model of the U.S. economy) developed by the Sandia National Laboratories has long played an important role in energy policy research [10]. Individuals in the ASPEN model represent real-life economic decision-makers, including households, banks, government, the Federal Reserve, and firms. In the field of computational economics, AMES is used to simulate spot electricity market transactions based on node price [11].

Just in terms of quantity, there is no shortage of energy or economy simulation tools, but to study dynamic interactions between different sub-systems their integration in one simulation environment is necessary [12]. A coupled simulation that combines a bottom-up/top-down approach shows its potential in energy–economy–environment (3E) prospective modeling, which is worthy of attention [13]. Current research attempts to achieve coupled simulation by connecting different simulation tools [14]. For instance, in [15], a soft-linking of a power systems model to an energy system model is presented. Both models exist as themselves in a simulation system, i.e., PLEXOS [16] and TIMES [17]. Furthermore, in [18], an architecture that tries to encompass any tool that aims to model the energy sector is proposed. Distributed simulation offers strong computing power and less computing time based on multi-thread simulation technology. These features are the reasons distributed simulation is widely used in complex system simulation. It is difficult to implement parallel simulation through the joint simulation of software connections due to limitations of interface authority. In addition, the data format or application interface of each system is different, and each application must develop special data interface conversion programs for other applications to realize information sharing. In the absence of a common data interface/model, the number of data converter programs required by N applications is $C_N^2 = \frac{N \cdot (N-1)}{2}$, which requires significant human effort to implement mappings.

Regarding a model specification formalism, generic and scalable models have also received considerable attention. Modelica [12] is an open, object-oriented, equations-based language that can only model complex physical systems across different fields. PRIMES is a 3E model developed by E3M-Lab in the institute of Communication and Computer Systems of the National Technical university of Athens [19], and its objective is to simulate energy systems and markets across Europe. The model in PRIMES provides detailed descriptions, including of energy production, emissions, and market, but it still does not involve more elaborate operations models, such as transient models. The Common Information Model (CIM), which is currently modeled as a UML, allows application software to exchange information about power systems [20] and energy market data [21]. It has been widely used in the field of power system modeling but not used in a general energy–economy coupled system. There are also optional agent development frameworks that can be adopted to code the simulation, but the programmer still must define the non-standard and user-defined model of

the agents by writing code in a programming language. Thus, a unified modeling and simulation approach that is easily implemented is needed. Odell and Giorgini [22] summarized the existing meta-models of multi-agent systems from the perspective of software engineering, which attempts to propose a unified multi-agent model.

The simulation of EECS has four characteristics. First, almost all existing components in a system may change their intrinsic properties over time, such as the technical arguments, evolving behavior, and acquired data. Second, as a broad cross-disciplinary approach capable of capturing system-wide interdependencies [23], such a simulation system contains a large number of individuals and requires a broader modeling scope, not only with respect to energy devices, but also active market players. Third, interactions between individuals exist universally [24]. Fourth, the time-varying characteristics of individuals vary greatly, so that multiple simulation timescales coexist, from long-term investments and de-carbonization strategies to short-term operational and even transient process aspects of systems.

Regarding the aforementioned characteristics, requirements for simulation platforms of EECS are introduced. First, the platform should adopt a general and extensible model or interface that can be compatible with different types of individuals to facilitate the easy design and development of simulations. Second, the platform should enable parallel computing to decompose computing tasks. Because the simulation system contains a large number of individuals whose decision-making may be very complicated, and some small-step simulations have high calculation frequency, the amount of calculations is very large, so that parallel computing and distributed simulation are needed. Third, multiple-timescale simulation deserves strong support for different frequency individual characteristics, considering long-term perspectives as well as short-term operational details. Fourth, the platform requires dynamic simulation ability for complex adaptive systems.

The individual-based model (IBM) is widely applied in ecology [25]. The authors of [26] proposed a standard protocol called ODD (Overview, Design, and Details) to describe simulation models in the field of ecology. When ODD was proposed, it was intended to solve the problem of irregular complex model descriptions of ecology research papers in the case of limited space in academic journals. The protocol consists of three components: the overview, design concepts, and details. In the overview, the purpose of simulation, simulation variables, simulation scale, simulation step size, simulation calculation order, and other simulation information are included in detail. Design concepts contain a number of concepts. Details contain the simulation initialization configuration data, input data for the external environment, and the calculation subprocesses. The ODD protocol is a good idea that has been applied in many subsequent studies, and has been improved in a later updated version [27]. Energy–economy coupled systems comprise a complex system similar to an ecosystem, and the ODD protocol can also be used to describe simulation models of energy–economy systems. However, to adopt this protocol as a computable data model, many improvements must still be made, because it is not designed as a canonical computing model for the simulation of EECS, but rather a model for document description. In [28], attempts are made to apply the IBM in system dynamic analysis and the result shows that IBM can work well in IESs. At the same time, the IBM has superior characteristics, e.g., it is distributed and privacy-protected. The cross-disciplinary trend makes model compatibility necessary and possible, mainly through general software and standard protocols. In such a context, building a simulation platform suitable for the IBM must also be considered.

In summary, the IBM has the following characteristics: First, it describes a single entity, not the entire simulation system. This feature is in line with the bottom-up modeling idea, and can realistically describe the model details, resulting in the “emergent” behavior of the system. Second, the IBM is standardized in that it has a fixed form that applies to a wide variety of individual descriptions. Third, it is distributed compared to the centralized model. The IBM is expected to be applied more in the current climate of distributed research. Fourth, the IBM protects privacy. In the EECS, there are different interest subjects that put forward the requirement of information protection. The data contained in the IBM are readable only to subjects who have access to it, helping to protect individual privacy. Therefore, compared with existing models and tools, the proposed approach is more versatile for the cross-disciplinary EECS and has better compatibility with multiple models with significantly different characteristics. Moreover, the distributed idea makes it easier to decompose complex systems into multiple sub-parts, which interact with each other through communication. The decoupled IBM is used to realize the coupling simulation, which can not only adapt to the privacy protection needs of the energy market research but also study the overall performance of the whole system. A detailed technology characteristics comparison between the popular M&S methods and the proposed method is shown in Table 1. By comparison, we can see that the PRIMES is excellent among multiple existing methods. However, compared with the proposed method, it still lacks standardized model form, more compatible multi-scale time simulation, and adaptive distributed simulation ability. In Appendix A, the SWOT analysis matrix of the proposed method is presented (see Table A1).

For the reasons given above, in this paper, an attempt is made to address the two key issues in simulation and modeling aspects, considering that the IBM has the characteristics of being distributed, standardized, generalized, and to offer privacy protection. The main contributions of this paper are the following. (1) A review of the current state of simulation in the energy–economy field, including methods, tools, and shortcomings. (2) It improves the standardization with a proposed superstructure specification; that is, the modified IBM, consisting of a multi-tuple, which is defined and proved to be applicable to energy–economy coupled systems. In addition, an abstract interface is designed for a customized model solver. (3) Another forward-looking aspect of this study is to propose a coupled system simulation method that can be compatible with different simulation step sizes. (4) A programmable implementation scheme is provided. (5) A use case is designed to illustrate how the IBM works when applied in energy scenarios. The remainder of this paper is organized as follows. IBM and its general structure are explained, in particular, a full description of the elements of IBM, in Section 2. In Section 3, the simulation approach suitable for the IBM is presented. In Section 4, an implementation of simulation platform is described. Simulation results from runs of the proposed model and method, as well as its related analysis, are also presented in Section 5. Finally, conclusions and future prospects are given in Section 6.

Table 1. The feature comparison of various modeling and simulation methods in the energy economy field.

	MARKAL (MARKet Allocation Model) [3]	MESSAGE (Model for Energy Supply Strategy Alternatives and Their General Environmental Impact) [29]	PRIMES (Price-Induced Market Equilibrium System) [19]	POLES (Prospective Outlook on Long-Term Energy Systems) [30]	OSeMOSYS (Open Source Energy Modelling System) [31]	LEAP (Long-Range Energy Alternatives Planning System) [32]	The Proposed Method
Methodology	Bottom-up	Bottom-up	Hybrid	Hybrid	Bottom-up	Hybrid	Bottom-up
Model classification	Mathematical programming [33]	Mathematical programming [34]	Simulation	Econometric [35]	Mathematical programming	Accounting	Simulation
Model scope	Energy sector only	Energy sector only	European energy sector and its market [19]	Mainly energy supply and demand sectors	Energy sector	Energy and climate sector	Energy economy system
Dynamic simulation	Unsupported	Unsupported	Supported	Supported	Supported	Unsupported	Supported
Model standardization	Personalized	Personalized	Personalized	Personalized	Personalized [36]	Personalized	Formalization
Privacy protection	Poor	Poor	Good	Poor	Poor	Poor	Good
Time horizon	Medium, long term	Medium, long term [37]	Long term up to 2070	Up to 2050 [30]	Long term	Medium, long term	Short, medium, long term
Time step	User-defined	5 or 10 years [37]	Yearly	Yearly	Yearly	Yearly	User-defined
Interaction method	Hard-linked	Soft- and hard-linked	Soft-linked	Hard-linked	Hard-linked	Unknown	Soft-linked
Distributed or parallel technology	Unsupported	Unsupported	Unsupported	Unsupported	Unknown	Unsupported	Supported
Visualization	Unknown	Unknown	Unsupported	Unsupported	Unsupported but the third part interface available [38]	Supported	Supported
Language or software	GAMS [3]	FORTTRAN [29]	Unknown	Vensim software required [39]	MathProg and being translated into GAMS and Python [40]	MathProg	JAVA/JADE
Scalability	Ordinary	Ordinary	Good	Ordinary	Good [31]	Ordinary	Good

Interaction method: a coupling of existing models (“soft-linked”) or a single integrated model which blends features of both top-down and bottom-up models (“hard-linked”).

2. IBM for EECS Simulation

An IBM models not only energy physical systems, but also energy economic, social, and cyber systems that affect the physical system. Therefore, the individual may be a physical device, financial market, data interface, or even a test rag. Almost all individuals can be modeled using an IBM. In addition, multiple relationships exist among individuals, resulting in individuals in the IBM of an EECS at different scales. For example, a thermal power plant individual usually contains more than one generator unit individual. Furthermore, each generator unit individual contains sub-units, such as exciter, steam turbine, and heat pump individuals. Figure 1 shows a common energy–economy coupled scenario consisting of multiple individuals of different types and sizes. Using mathematical set theory, the IBM can be formulated as Equations (1) and (2) in the form of five-tuples. The model describes individuals in detail without redundant data:

$$\Sigma = (\mathbf{I}, \mathbf{M}, \mathbf{S}, \mathbf{F}, \mathbf{O}) \quad (1)$$

$$\mathbf{M} = (\text{ID}, \text{T}, \mathbf{A}, \mathbf{C}, \mathbf{W}), \quad (2)$$

where Σ denotes any target individual or component; $\mathbf{I}$ and $\mathbf{O}$ denote individual's inputs and outputs; and $\mathbf{M}$ denotes static model of the individual that presents inherent attributes, including a globally unique identifier (ID), type (T), argument set ($\mathbf{A}$), connectors ($\mathbf{C}$), and subset ($\mathbf{W}$). $\mathbf{S}$ is an individual's state set and $\mathbf{F}$ denotes the function set that defines an individual's dynamic behavior. All elements are described in detail below.

Figure 1. Multiple individuals with different types and sizes in energy system.

2.1. Input and Output

$\mathbf{I}$ and $\mathbf{O}$ are coupling artifacts among multiple individuals. Specifically, $\mathbf{I}$ means their external input events that describe environmental conditions and $\mathbf{O}$ means that an individual can also post external output events. $\mathbf{I}$ and $\mathbf{O}$ in Equation (3) denote an individual with m inputs and n outputs, respectively:

$$\begin{aligned} \mathbf{I} &= \{x_1, x_2, \dots, x_m\} \\ \mathbf{O} &= \{y_1, y_2, \dots, y_n\}. \end{aligned} \quad (3)$$

During the simulation, an individual will provide updated values for the output variables, which serve as input variables for other individuals. The contents of input and output are multiple

flows, including information flow, cash flow, and energy flow. Information flow represents information exchanged between individuals, such as price information that an exchange publishes to market participants. Cash flow represents the financial income or expenditure generated by the activities of individuals. Energy flow represents the energy production and consumption at the physical mechanism level, and it obeys the fundamental laws of physics, such as *the conservation of energy* and *Kirchhoff's laws*.

During the actual modeling process, one can also do some special processing on individual input and output. For example, a source can be regarded as an individual with no input and n outputs. A sink can be regarded as an individual with m inputs and no output. A converted individual (such as a transformer) can be seen as an individual with m input and n outputs [41].

2.2. Static Model

The static model **M** describes the general and characteristic parameters of an individual with five elements, namely ID, T, A, C, and W, as shown in Equation (2). ID (identification) is a means to identify an individual and it should be immutable and globally unique. It can be expressed by a name or sequence number so that any one individual will be marked with $\sum_{ID}$. T (type) denotes the classification of individuals corresponding to the conception *Class* in object-oriented programming. A (arguments) are some values that describe individual characteristics. C (connector) reflects a mapping between inputs and outputs. In addition, connectors have two basic functions, namely translation and arithmetic for the three kinds of flows: energy flow, information flow, and cash flow. It must be emphasized that energy flow and cash flow are usually expressed by a sum-to-zero equation, while information flow is expressed by trivial identity equations that are seen as comprising lossless transfer. W represents included or belonging relationships between individuals. If an individual has no child individual, W can be represented by $\emptyset$.

2.3. State

Regarding an individual, two key components exist in its internal structure: the state and its transition mechanism. State denotes a condition in which an individual must meet certain requirements, perform certain actions, or wait for certain events. The state set includes all states in the lifecycle of an individual. At the same time, the state transition mechanism shows how a state is transferred to a successor state, which is explained in Section 2.4.

2.4. Function

Function specifies the way in which states and variables are modified. It consists of three key functions: the time advance function ($ta()$), state transition function ($st()$), and output function ($y()$). In a single simulation step, an individual itself makes output and interaction decisions according the initial state by carrying $y()$ in the first place. Subsequently, its state is updated by $st()$. Finally, simulation logic time is pushed to the next step by $ta()$. State trajectory is determined by input x and initial state $s(0)$.

The state at the next time instant ($t + \lambda$) is expressed by Equation (4):

$$s(t + \lambda) = st(s(t), x(t)), \quad (4)$$

where λ is the simulation step size. Thus, it can be concluded that output trajectory $[y(t)]$ can be given by Equation (5):

$$y(t) = y(s(t), x(t)). \quad (5)$$

For a physical individual, $y()$ usually is a simple reflection such as a control signal. Regarding a decision maker individual, $y()$ often is polymorphic.

3. Simulation Approach Compatible with Different Simulation Step Sizes

In the real world, different individuals have different time-varying characteristics. Taking the individual model of a multi-energy system as an example, there are power system individuals with rapidly changing electromagnetic characteristics, as well as natural gas and thermal system individuals with slowly changing characteristics. To describe various dynamic characteristics, different timescales should be used to model these objects in the simulation model. At the same time, there are both macro models with a relatively long timescale and micro models with a short timescale in economic models. In particular, continuous time simulation and discrete time simulation may exist in the same system; for the former, individuals can usually be described by the basic laws of physics in a differential equation model manner, while, for the latter, the individual logic time can jump from t_1 to t_2 , ignoring the time in between. In environmental and ecological science, a hybrid bottom-up/top-down simulation is also widely used to represent complex, integrated systems of social and technological components, as in [42,43]. When all of these simulation models with different timescales exist in the same simulation system, the synchronization of simulation time between individuals must be addressed.

In this paper, a multi-scale time simulation approach compatible with different simulation step sizes is adopted. During simulation, different individuals may run independently for several time intervals and individual behaviors are executed in parallel; the value of the coupling variables are exchanged at a defined logic time called a macro-time step (MTS) [44]. After pushing one MTS, an output variable will be sent to the individual that has input with the same name. A different time step may be adopted internally, called a micro-time step (μ TS). The synchronous method is explained by Figure 2. Taking three individuals $\Sigma_1, \Sigma_2, \Sigma_3$ with different simulation step sizes $\lambda_1, \lambda_2, \lambda_3$, all individuals initialize their logic time at t_0 . The first interaction occurs between Σ_1 and Σ_2 at $t_{1,2}$ when Σ_1 has pushed i steps and Σ_2 has pushed j steps. Thus, $t_{1,2} = i * \lambda_1 = j * \lambda_2$. Regarding $t_{1,2,3}$, three individuals interact with one another, and Σ_2 and Σ_3 have pushed n, k steps, respectively. Here, $t_{1,2,3}$ is the lowest common multiple of $\lambda_1, \lambda_2, \lambda_3$, and $t_{1,2,3} = n * i * \lambda_1 = n * j * \lambda_2 = k * \lambda_3$.

Figure 2. Individual interaction moments with different simulation step sizes.

The mathematical expression of the interaction time (T) for any two individuals the step sizes of which are λ' and λ'' , respectively, is the following (Equation (6)):

$$T = \{ t \mid t \% \lambda' = 0 \ \& \ t \% \lambda'' = 0 \}. \quad (6)$$

4. Implementation

As shown in Figure 3, the proposed simulator is implemented with a hierarchical framework adopting Java, an object-oriented programming language. In this way, polymorphism and inheritance techniques can be used to realize reuse and extension. A Java virtual machine (JVM) is located between the operating system (OS) and Java agent development framework (JADE). This feature enables the emulator to function across platforms. JADE plays a role of communication between individuals and is located in the communication layer. Based on the IBM definition and object-oriented programming practice, the unified modeling language (UML) class diagram of the extensible IBM is presented as Figure 4. Extensible markup language (XML) is adopted for data modeling considering its standard and extensible form of expression. For the sake of individual-based simulation, component modeling can be implemented by visual interface actions such as dragging, dropping, and linking, with the help of third-party libraries such as JGraph [45]. It should be noted that JGraph is implemented on the basis of the model–view–controller architecture so that the model can be filled with the IBM directly without additional efforts. JFreeChart is an open charting class library on the Java platform, and with its help many kinds of charts can be generated, so that individual internal state and input or output indicators can be viewed. The visual modeling interface consists of five main panels, including the graphical modeling panel, component library, five-tuple configuration dialog, run monitor interface, and JADE manager. Among these panels, frequently used models are built into the component library panel, which can be added to the graphical modeling panel. In addition, the five-tuple configuration dialog provides an interface for setting up IBM data. The run monitor and JADE manager interface are responsible for individual indicator monitoring and JADE communication management, respectively.

Figure 3. Simulator hierarchical framework.

Compared with other simulation platforms (mainly centralized standalone platforms), the proposed simulation platform can run on multiple hosts in a distributed manner, based on the above design and implementation methods. This can reduce performance requirements (such as memory and central processing unit) on a single machine. Based on experience, researchers can distribute the computational load of the system evenly across multiple hosts. In particular, we encourage researchers to take full advantage of multithreading and parallelism, which is supported by the simulation platform designed in this paper. The benefits are reflected in two aspects, one is different individuals can take up a thread to carry a task. Another is individual inner can also deal with parallel behavior. At the same time, the simulation times on different computers are synchronized according to the method in Section 3, to maintain the consistency of simulation times.

Figure 4. UML class diagram of IBM.

5. Case Study

Energy–economy coupled scenarios can be explored by building a series of IBMs that contains goals or constraints of a system individual. A scenario is introduced in this section to further clarify the application of the proposed model and method. The experiments were performed using a mid-range consumer laptop (Intel i5, 1.8 HZ and 8 G memory) to run the code and the visual interface, which also functioned as a data-logger.

As shown in Figure 5, based on data presented in [46] and a modified IEEE three-machine system, a test system was conceived and outlined that contains heating and electricity. It is assumed that a co-generator (G_2) is located at bus 2 (B_2) and another two routine generators (G_1 and G_3) are located at buses 1 and 3, respectively. G_2 provides a heating stream for the comprehensive load (L_1) at bus 4 (B_4) through a hot water pipeline without considering transmission loss. Figure 6 shows the thermal and electrical output feasible region of G_2 , which is described as a polygon [46]. In addition, G_1 and G_3 only provide the system with electricity. Regarding energy consumption, the consumer at B_4 is a comprehensive consumer having both heating and electrical demands. What needs to be illustrated here is that the heating demand can be met by water-heat radiators and an electric heater. Therefore, L_1 at B_4 must decide the volume of heating and electricity (d_{t,L_1}^h, d_{t,L_1}^e) to be purchased according to the published locational marginal price (p_{t,L_1}^e) and preset heating price, as well as its maximized utility function (Equation (9)). Parameters μ_h, μ_e, σ_h , and σ_e in Equation (9) are coefficients of heating and the electricity utility function, respectively. $v_{t,i}^h, v_{t,i}'$ and $v_{t,i}''$ are decision variables, and k is the efficiency of the electric heater. d_{t,L_1}^e consists of two parts: demand of non-heating electrical load (d_{t,L_1}') and demand of the electric heater (d_{t,L_1}''). Therefore, total electrical demand $d_{t,L_1}^e = d_{t,L_1}' + d_{t,L_1}''$ for L_1 . The load at bus 5 (L_2) and bus 6 (L_3) are purely non-heating electricity loads.

Figure 5. Topology of test system.

Figure 6. Co-generator heat-power output feasible region: A (32.4, 125.8); B (135.6, 110.2); C (75, 40); D (15.9, 44), E (0, 44); and F (0, 125.8).

At the beginning of the t th iteration, L_1 informs G_2 of its heating stream demands (d_{t,L_1}^h). G_2 operates in the “electricity follows heating” mode to meet heating demand with adequate supply. Then, all of the loads submit their demands to the independent system operator (ISO) while generators report their marginal linear supply curve [47]. ISO performs the economical dispatch based on the optimal direct current flow and returns clearing results to each individual. Directly after that, each load individual participates in a new round of market and repeats the cycle according to the clearing price (p_{t,L_i}^e). Similarly, all generators formulate their supply curve based on the clearing volume (v_{t,G_i}^e).

Usually, the cost of a co-generator (e.g., c_{G_2}) can be expressed as a multinomial of Equation (7), in which a_0, a_1, a_2, a_3, a_4 , and a_5 represent coefficients of cost. In this paper, $a_0 = 2650, a_1 = 14.5, a_2 = 4.2, a_3 = 0.0345, a_4 = 0.03$, and $a_5 = 0.031$. Letting $v_t^h = 0$ represent the cost of a traditional generator (i.e., G_1 and G_3), one can arrive at the marginal cost of electricity production of G_2 , i.e., (8), as well as its supply curve, Equation (11):

$$c_{G_2} = a_5 v_{t,G_2}^e d_{t,L_1}^h + a_4 (d_{t,L_1}^h)^2 + a_3 (v_{t,G_2}^e)^2 + a_2 d_{t,L_1}^h + a_1 v_{t,G_2}^e + a_0, \quad (7)$$

$$c'_{G_2} = a_5 v_t^h + 2a_3 v_t^e + a_1, \quad (8)$$

$$\begin{aligned} \arg \max_{(v_{t,L_1}^h, v'_{t,L_1}, v''_{t,L_1})} & -\frac{1}{2} \mu_h (v_{t,L_1}^h + k v''_{t,L_1})^2 \\ & -\frac{1}{2} \mu_e (v'_{t,L_1})^2 \\ & + \sigma_h (v_{t,L_1}^h + k v''_{t,L_1}) + \sigma_e v'_{t,L_1} \\ & - p_{t,L_1}^h v_{t,L_1}^h - p_{t,L_1}^e (v'_{t,L_1} + v''_{t,L_1}) \end{aligned} \quad (9)$$

The utility functions of L_2 and L_3 are given by the following formulation (Equation (10)):

$$\arg \max_{v_{t,L_i}^e} -\frac{1}{2} \mu_e (v_{t,L_i}^e)^2 + \sigma_e v_{t,L_i}^e - p_{t,L_i}^e v_{t,L_i}^e, \quad (10)$$

$$\begin{cases} a_{t,G_1} = a_5 v_t^h + a_1 \\ b_{t,G_1} = 2a_3 \\ p_{min} = \min\{y | (v_t^h, y) \in R\} \\ p_{max} = \max\{y | (v_t^h, y) \in R\}, \end{cases} \quad (11)$$

$$\mathbf{N} = \begin{bmatrix} 2 & 6 & 550 & 0.072 \\ 3 & 6 & 240 & 0.101 \\ 2 & 4 & 240 & 0.161 \\ 3 & 5 & 240 & 0.170 \\ 4 & 1 & 240 & 0.085 \\ 5 & 1 & 240 & 0.092 \end{bmatrix} \quad (12)$$

The IBMs of the simulation case are listed in Table 2, in which $\mathbf{R}$ is the output feasible region of G_2 and $\mathbf{N}$ is the power network topology matrix, which is represented by a matrix as Equation (12). Each row of the matrix represents branch information of the transmission line, and the four columns of data represent the start bus number, end bus number, capacity, and reactance of the line, from left to right. Σ_{EH} , Σ_{EL} , and Σ_{WH} represent electric heater individual, electricity load individual, and water-heat radiators individual, respectively. Σ_N is the power network individual. WAIT and DECISION in the table means two finite states of the individual. WAIT & DECISION in the table means two finite states of the individual. p_{min} and p_{max} are the generator's maximum and minimum generating capacity, respectively.

It is easy to see that the IBMs in Table 2 have the same data structure and interfaces and require only minor modifications. This will make it possible to reuse the model, greatly reducing the modeling effort. Figure 7 shows demand volume of comprehensive consumers for each delivery cover, including heating steam, non-heating electricity load, and electric heater. As can be seen in the figure, non-heating electricity load reaches up to the high value of 106.8 MW at the third iteration. Then, a drop occurs, followed by a slight rise from 102.8 to 103.0 MW. Upon changing the steam price from 21.0 to 18.0 \$/MWh, it is seen that a low electricity price leads to more electricity purchased for electricity consumption and replacement, as shown in Figure 8. Because of the coupling of power and heat by the co-generator, the electrical consumption demand has also changed. It is necessary to note that 30.0, 60.0, and 0.0 MW were set as the initial values for v_{t,G_1}^h , v_{t,G_1}'' , and v_{t,G_1}^e , respectively. When the initial values were changed to 35.0, 50.0, and 10.0 MW, a steady state is realized in a few iterations, as shown in Figure 9. As shown in Figure 9, we changed the initial demand value without changing the steam price and found that the system reached the same equilibrium after several iterations, indicating

that the same equilibrium value can be obtained from different initial values. This is consistent with the common knowledge of research in this field. To a certain extent, it verified the effectiveness of the simulation model and method.

Table 2. Individual model elements.

	Σ_{L_1}	$\Sigma_{L_i} (i = 2, 3)$	$\Sigma_{G_i} (i = 1, 3)$	Σ_{G_2}	Σ_O
I	p_{t,L_1}^h, p_{t,L_1}^e	p_{t,L_i}^e	v_{t,G_i}^e	$d_{t,1}^h, v_{t,G_2}^e$	$a_{t,G_i}, b_{t,G_i}, d_{t,L_i}^e, p_{max}, p_{min}$
	ID L_1	L_2	G_i	G_2	O
	T Comprehensive Consumer	Consumer	Generator	Co-generator	ISO
M	A $\mu_h, \mu_e, \sigma_h, \sigma_e, k$	μ_e, σ_e	P_{min}^i, P_{max}^i	R	N
	C C_{G_2}, C_O	C_O	C_O	C_O, C_{L_1}	C_{L_i}, C_{G_i}
	W $\Sigma_{EH}, \Sigma_{EL}, \Sigma_{WH}$	$\emptyset$	$\emptyset$	$\emptyset$	Σ_N
S	WAIT, DECISION	WAIT, DECISION	WAIT, DECISION	WAIT, DECISION	WAIT, DECISION
F	Equation (9)	Equation (10)	Equations (8) and (11) and $v_t^h = 0$	Equations (8) and (11)	$\min \sum_{i=1}^3 c_{G_i}$
O	$d_{t,1}^h, d_{t,1}^e$	$d_{t,i}^e$	a_{t,G_i}, b_{t,G_i}	$a_{t,G_2}, b_{t,G_2}, p_{max}, p_{min}$	$v_{t,i}^e, p_{t,i}^e$

Compared to the centralized modeling approach, the IBM approach requires several interactions to reach equilibrium and may have a relatively inefficient optimization process or result because it does not have sufficient global information. At the same time, it is difficult to verify the high complexity problem mathematically. However, the distributed evolution process is still considered in the existing research to be a more realistic reflection of the dynamic process in the real world.

Figure 7. Dynamic equilibrium is reached after several iterations.

Figure 8. When the steam price changes after the sixth iteration, the mix of energy demand changes.

Figure 9. Dynamic equilibrium is still reached, even if the setting of the initial value has changed.

6. Conclusions

To summarize, considering the characteristics and requirements of the simulation of the EECS, this study obtained a suited IBM by defining standardized structures and elements. Following the bottom-up modeling idea, the IBM can be used to model each and every individual, no matter how complex or simple they are. In particular, it can work with multiple-timescale models, which is valuable for research on time-varying systems. Moreover, the reserved interface is an important feature of the IBM, which makes the IBM model more applicable, considering there is no universal algorithm for all individuals, both physical and social. In addition, a practical programming implementation method is developed that helps lower the threshold for beginners. According to the simulation case presented in this paper, the simulated target system can be represented by a regular and clear IBM set, which helps to reuse and globalize the model. In addition, the proposed method can describe the individual dynamic characteristics in the energy–economy coupled simulation scenario, and the simulation platform can clearly observe the dynamic process of the system. All these efforts aim

to obtain a systematic approach that can help find better solutions for energy and environmental problems at the intersection of energy techniques, market economy, environmental protection, and human society. Although this work describes completion of the major portion of work in design and implementation, to show its significance, the model, method, and platform form a complete simulation architecture that is worthy of further improvement. At the same time, considering that the proposed method in this paper supports distributed simulation technology, it is valuable and promising to adopt a real complex system for modeling in our future research work.

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Appendix A

A hierarchical individual illustration is shown in Figure A1.

Figure A1. Hierarchical individual illustration.

The SWOT analysis matrix of the proposed method is shown in Table A1.

Table A1. The SWOT analysis matrix of the proposed method.

	Strengths 1. Standardized and formalized model 2. Flexible time scale 3. Distributed and parallel technologies inclusion 4. Dynamic simulation inclusion	Weaknesses 1. Difficult mathematical theory validation
Opportunities 1. Distributed technologies are in vogue 2. Interdisciplinary studies are highly valued 3. Energy markets are being implemented widely 4. Dynamic simulation is considered to be more realistic than pure centralization mathematical optimization	Opportunity–Strength strategies (use strengths to take advantage of opportunities) 1. Standardized models can be used to model multidisciplinary models uniformly 2. Multi-scale time simulation can adapt to different models with different characteristics 3. It is promising to integrate distributed frontiers, such as algorithms, models, databases, and so on 4. Dynamic simulation is helpful to understand the system characteristics	Opportunity–Weakness strategies (overcome weaknesses by taking advantage of opportunities) 1. Seeking support from decentralized optimization and game theory
Threats 1. The target system becomes more and more complex	Threat–Strength strategies (use strengths to avoid threats) 1. Decomposition modeling complex systems based on individual model 2. Distributed parallel technology can improve simulation performance	Threat–Weakness strategies (minimize weaknesses and avoid threats) 1. Delimit boundaries of the research and M&S

A visual modeling interface illustration is shown in Figure A2.

Figure A2. Simulator process visual modeling interface.

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