Knowledge Processing Studies. 2024, 4(2): 13-27.

International Journal of Knowledge Processing Studies
(KPS)

Homepage: http://kps.artahub.ir/

ORIGINAL RESEARCH ARTICLE

Data-Oriented Model of Gas Consumption Management Emphasizing the Issue of Unauthorized Use Based on Information Systems Analysis

Ali Esmaili[1], Hoshang Taghizadeh[2*], Naser Faqhi Farhamand[3]

[1] *PhD student of Industrial Management, Tabriz Branch, Islamic Azad University, Tabriz, Iran. esmailiali023@gmail.com*
[2] *Professor, Industrial Management, Tabriz Branch, Islamic Azad University, Tabriz, Iran. (Corresponding Author) taghizadeh46@yahoo.com, 0000-0003-4160-9157*
[3] *Associate Professor, Department of Management, Tabriz Branch, Islamic Azad University, Tabriz, Iran. saudatmand@khuisf.ac.ir, 0000-0001-6263-4787*

ARTICLE INFO

Article History:
Received: 2023-06-26
Revised: 2023-07-16
Accepted: 2023-09-17
Published Online: 2024-03-01

Keywords:
Gas Consumption Management, Data-Oriented Model, Information Systems, Gas Company, East Azerbaijan Province.

*Number of Reference:*36
Number of Figures: 1
*Number of Tables:*3

DOI:
10.22034/kps.2023.404190.1146

ABSTRACT

This research aims to study the data-driven model of gas consumption management, with a focus on addressing unauthorized use through the analysis of information systems. Research was conducted using a metasynthesis approach and technique in the field of gas consumption management and mathematical programming with genetic algorithms. ATLAS.ti software was used for analysis. The influencing factors related to a specific period of time were examined and searched for in this research. Internal and external sources from the years 2006 to 2023 were analyzed. 27 studies were selected based on the Critical Appraisal Skills Programme (CASP) technique. In the continuation of mathematical modeling using MATLAB software, the simulation was conducted to compare the performance of three proposed algorithms. Based on the results obtained from the meta-combination technique, the main categories include the use of renewable energy, gas consumption management, shortcomings, obstacles, data-driven solutions, consequences of gas consumption management, and economic growth. All three models also demonstrated the basis for optimal gas consumption and the reduction of unauthorized consumption. The utilization of data analysis can enhance system efficiency, pinpoint weaknesses and losses, boost productivity, and optimize the utilization of gas energy. Based on the analysis, it was shown that data mining can be very useful in managing gas energy consumption and identifying unauthorized breaches. Overall, simulating gas energy consumption management using a genetic algorithm can provide efficient and effective solutions, handle complex and dynamic scenarios, and offer insights into optimizing gas consumption and energy efficiency. **©authors**

►**Citation:** Esmaili, A., Taghizadeh, H., & Faqhi Farhamand, N. (2024). Data-Oriented Model of Gas Consumption Management Emphasizing the Issue of Unauthorized Use Based on Information Systems Analysis. *International Journal of Knowledge Processing Studies (KPS)*, 4(2): 13-27. Doi: 10.22034/kps.2023.404190.1146

1. Introduction

Data-based gas energy consumption management includes the use of gas consumption data in order to improve efficiency and reduce energy waste in gas systems (Wu et al., 2023). To manage gas energy consumption based on data, it is necessary to collect gas consumption data in different systems. These data can include the volume of gas consumed, time of use, pressure and temperature, seasonal changes, and other characteristics related to gas consumption (Vali et al., 2022). Using the collected data, it is possible to analyze patterns, trends, and weak points related to gas consumption. This analysis can be done using statistical methods and machine algorithms. For example, it is possible to identify gas consumption patterns during rush hours or according to the variables of air temperature and days of the week (Qiang et al., 2022). Using historical gas consumption data, it is possible to predict consumption patterns and help match consumption with demand. This prediction can help in the optimal planning of gas production and distribution as well as better control of energy consumption. It is possible to provide the necessary announcements and awareness to the users. These announcements can include high energy consumption, loss warnings, or orders to improve gas efficiency (Liu et al., 2021).

By analyzing gas consumption data and identifying weak points, measures can be taken to optimize energy consumption. These measures can include improving equipment performance, setting optimal pressure and temperature, and using smart systems and remote control (Sharma et al., 2022). In general, data-based gas energy consumption management can help reduce costs, improve efficiency, and reduce environmental impacts associated with gas energy consumption.

Identifying unauthorized gas branches with a data-driven approach can help identify and control gas misuse in gas distribution systems (Tam et al., 2021). The first step to identifying unauthorized gas distributions is to collect data related to the gas distribution system (Tusher et al., 201. These data can include authorized gas consumption, gas pressure, temperature, gas flow rate, and communication data such as place and time of consumption. Using the collected data, it is possible to analyze the patterns, trends, and inspirations related to authorized gas consumption. Based on the existing patterns, it is possible to identify and separate unauthorized branches and take the necessary measures to control them. Using intelligent algorithms. Based on the data, unauthorized consumption patterns can be detected. These algorithms can detect unauthorized branches and report disturbances to system administrators using machine learning, neural networks, decision trees, and other algorithms (Mischos et al., 2023).

By comparing gas consumption data over time, sudden and unusual changes can be detected. These changes may indicate illegitimate branching that should be investigated and controlled (Liu et al., 2023). Intelligent systems equipped with sensors and communication networks can have a major improvement in identifying unauthorized gas branches. These systems can detect suspicious changes early and announce the necessary measures to prevent gas abuse. By using the stated approaches, it is possible to help identify and control unauthorized gas branches in gas distribution systems and reduce the amount of energy wastage and the risks associated with them (Ahmad et al., 2022).

By using databases, it is possible to analyze gas energy consumption data and identify consumption patterns, trends, and weak points. This analysis can be done using statistical methods and machine algorithms and provide useful information about gas energy consumption and its different patterns. It is possible to predict gas energy consumption patterns and perform optimal planning for gas production and distribution. This prediction can help to improve the planning and control of gas energy consumption, thereby reducing costs and related environmental impacts. It is possible to identify unusual consumption patterns, weaknesses, and losses in the gas distribution system. This identification can help system managers to take appropriate measures to improve efficiency and reduce gas energy losses. Databases provide managers and officials with the ability to monitor and report accurately on gas energy consumption and system performance. These reports can help to improve decision-making and planning of gas energy consumption management and increase efficiency and productivity. It can be said that databases help in optimizing gas energy consumption by providing the necessary data, analyzing data, predicting consumption, and identifying relevant weaknesses and losses. They facilitate system performance improvement and efficiency improvement.

2. Literature Review

The gas industry is an important part of the country's economy, and the culture of energy consumption optimization is also affected by society's awareness of this industry as part of the general culture (Rahimi et al., 2022). Cultivation of optimal energy consumption is directly related to increasing knowledge about the amount of gas reserves, the processes of exploration, refining, transmission, and distribution, the measures taken to supply gas to households and production centers, and the costs of maintaining transmission and distribution networks, and the facilities and equipment required for continuous gas supply from one side. And the findings related to the optimization methods of energy consumption on the other hand and the role of this strategic product in industries and job creation and its effect on the political geography of the region. Most of the energy supplied in the country is consumed in industry and domestic consumption. The methods of optimal consumption management in the domestic and industrial sectors are different. Regarding energy management in the household sector, it is important to pay attention to the trend and how it is consumed in this sector (Boodi et al., 2018).

Databases play a very important role in optimizing gas energy consumption. These databases enable the collection, storage, and management of gas energy consumption data. Databases serve as central sources for collecting and storing data related to gas energy consumption. These data can include information such as gas consumption volume, consumption time, pressure and temperature, weather conditions, and other characteristics related to gas consumption (Varlamis et al., 2022).

Reviewing the research conducted, Adams et al. (2018), showed the importance of optimizing gas energy consumption and culturalizing the use of renewable energy. They discussed the importance of preserving the environment and reducing costs. Carroll et al. (2014), based on price and cost, presented a data-driven model for gas consumption management. Chen et al. (2023) showed that artificial intelligence is a suitable solution to preserve the environment based on energy consumption management. GAO et al demonstrated data-driven management in gas energy consumption by comparing energy consumption and valid decision-making based on data. Liu et al. (2023) introduced energy consumption prediction based on real data as one of the important methods of consumption management and detection of unauthorized branching.

Gas consumption management is a critical aspect of ensuring efficient and cost-effective operations in various industries. Unauthorized use of gas can lead to significant financial losses and safety concerns. Developing a data-driven model for gas consumption management with a focus on unauthorized use involves analyzing information systems and production processes. Here's a general outline of how such a model can be designed:

1. Data Collection: Gather relevant data on gas consumption from various sources, such as meter readings, production logs, and other relevant systems. This data may include timestamps, gas flow rates, pressure levels, and any other relevant parameters.
2. Data Integration: Integrate the collected data into a centralized data repository or data management system. This step involves cleaning and preprocessing the data, resolving

any inconsistencies or missing values, and ensuring data quality.

3. Feature Engineering: Extract relevant features from the integrated data that can help identify patterns and anomalies related to unauthorized gas use. These features may include consumption patterns during different production phases, historical usage trends, weather conditions, production output, or any other factors that may influence gas consumption.
4. Data Analysis: Apply statistical and analytical techniques to the collected data to identify normal gas consumption patterns and detect deviations or anomalies. This analysis may involve methods such as time series analysis, regression analysis, or machine learning algorithms, depending on the complexity of the problem and available data.
5. Model Development: Develop a predictive or prescriptive model that can identify and predict unauthorized gas usage based on the analyzed data. This model can be based on machine learning algorithms, such as anomaly detection algorithms, classification models, or clustering techniques, depending on the specific requirements of the problem.
6. Model Validation: Validate the developed model using historical data or simulated scenarios to ensure its accuracy and reliability. This step involves comparing the model's predictions with known instances of unauthorized gas usage to assess its effectiveness.
7. Implementation and Integration: Integrate the developed model into the existing gas consumption management system or information systems. This integration may involve real-time monitoring of gas consumption, generating alerts or notifications for unusual usage patterns, or integrating the model with other relevant systems for proactive gas consumption management.
8. Monitoring and Continuous Improvement: Continuously monitor the performance of the implemented model and collect feedback from users and stakeholders. This feedback can be used to refine the model, improve its accuracy, and adapt it to changing operational conditions or gas consumption patterns.

It's important to note that the specific implementation details and techniques may vary depending on the industry, organization, and available data. However, the outlined steps provide a general framework for developing a data-driven model for gas consumption management with a focus on unauthorized use

3. Methodology

In terms of the fact that the present research is looking for a data-oriented model of gas consumption management with an emphasis on the problem of unauthorized use based on data mining of a database based on a meta-synthesis approach, in terms of the general approach, it is a qualitative study and with a library research method, with meta-synthesis technique in the field of management. Gas has been consumed. ATLAS TI software was used for analysis. In response to this question, studies, articles, and theses of scientific databases were reviewed. Therefore, domestic and foreign sources related to 2006 to 2023 were examined. The metasynthesis method is used in the management and analysis of complex systems and problems. In this method, information and knowledge are collected from different sources and by combining and integrating them, a comprehensive and more complete view is presented for better analysis and understanding of the system or the subject under investigation.

In order to create a complete picture of the problem, the metacombination method includes the use of various concepts and tools. These concepts and tools may use different scientific and modeling disciplines and approaches. In fact, this method tries to take advantage of diversity and a diverse combination of methods and approaches to reach an integrated and inclusive analysis.

The advantages of using the hybrid method are:

1- Collecting and combining knowledge and information from different sources, which leads to a more complete picture of the system or the subject under investigation.

2- Creating connections and connections between methods and tools that help to better understand and critique the system.

3- Coping with complexity and uncertainty in systems, because the combination of different concepts and tools leads to greater ability to describe and analyze these types of systems.

The meta-composite method tries to provide a more comprehensive and complete analysis of a system or topic by combining various concepts and tools and takes advantage of the diversity of methods and perspectives.

4. Findings

As mentioned, the meta-synthesis analysis includes seven steps. In this section, the results related to each step of this analysis are presented separately.

The first step: Setting the basic questions of the research

The first step in Sandolowski and Barroso's method is setting research questions. These questions are generally based on four parameters: what, who, when, and how; It is adjustable. After the research questions are set based on the purpose of the research, the stage of a systematic review of the texts begins. Table 1 shows the answers to these fundamental questions related to the meta-synthesis method:

Table 1. Basic research questions

Parameter	Research question
What	Identification of energy management methods based on database
Who	Based on the specified keywords
When	Various works such as books, articles, reports in the field of energy efficiency based on the database
How	Including all the works in the years 2016 to 2023

The second step is the systematic review of the texts:

For the systematic study of the texts, the keywords related to this research include gas, optimal consumption, waste, illegal, and obstacles; Metasynthesis was reviewed in several domestic and foreign scientific databases, including Google Scholar, Science Direct, Civilica, Elmnet, Academic Jihad Scientific Information Center, Comprehensive Humanities Portal, and Irandoc, and related and suitable studies were extracted. In this step, the researcher managed to find 82 articles, which entered the third step of meta-synthesis for further analysis and final selection.

The third step of searching and selecting suitable articles:

In this step, the researcher rejected a number of articles in each review, which were not reviewed in the meta-synthesis process. In the review process, the researcher followed various parameters such as title, abstract, content, article details, etc.

The fourth step of extracting the information from the texts:

Throughout the meta-synthesis, the researcher continuously reviewed the selected and final articles several times in order to obtain the findings. In this research, the information and content of the articles were carefully checked and the reference of each article was recorded, and then the codes related to the keywords of energy management were extracted and categorized with a data-oriented approach. Entry criteria are specified based on keywords.

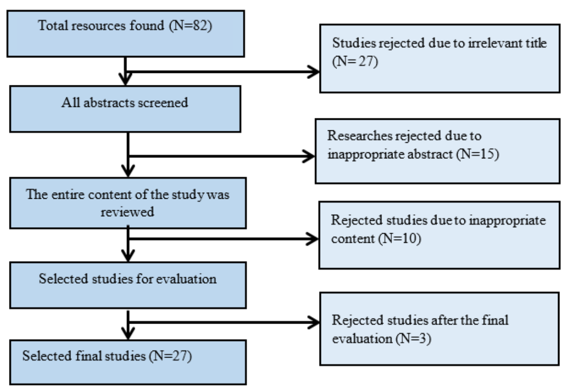

Fig1. Article selecting process

After removing the studies that are inconsistent with the objectives and questions of the research, the researcher must evaluate the methodological quality of the research. The purpose of this step is to eliminate researches in which the researcher does not trust the findings presented in them. A tool that is usually used to evaluate the quality of primary qualitative research studies is the "Critical Evaluation Skills Program" which helps to determine the accuracy, validity and importance of qualitative research studies by proposing ten questions. These questions focus on the following: 1. Research objectives 2. Methodological logic 3. Research design 4. Sampling method 5. Data collection 6. Reflexivity (which refers to the relationship between the researcher and the participation) 7. Ethical considerations 8. Accuracy of data analysis 9. Clear expression of findings 10. Value of research.

Table 2. Selected articles

CASP	Article	Code
40	Forecasting gas consumption of subscribers using data mining in Bushehr Gas Company	S01
35	.Design of integrated clustering-association data mining model to study the electricity consumption behavior of industrial units	S02
39	Presenting a model for predicting household gas consumption with the help of air temperature and number of subscribers	S03
40	Compilation of turning scenarios of natural gas consumers (case study: Mazandaran Gas Company)	S04
39	Data mining for energy systems: Review and prospect	S05
44	Forecasting annual natural gas consumption via the application of a novel hybrid model	S06
34	Carbon footprint forecasting using time series data mining methods: the case of Turkey	S07
32	Cooperative prediction method of gas emission from mining face based on feature selection and machine learning	S08
33	Care process optimization in a cardiovascular hospital: an integration of simulation–optimization and data mining	S09
37	Mining sensor data in a smart environment: a study of control algorithms and microgrid testbed for temporal forecasting and patterns of failure	S10
37	Dynamic slack-based measure model efficiency evaluation of the impact of coal mining characteristics	S11
33	Incorporating causality in energy consumption forecasting using deep neural networks	S12
35	Intelligent energy management systems: a review	S13
33	Smart fusion of sensor data and human feedback for personalized energy-saving recommendations	S14
38	Prediction of blast furnace gas generation based on data quality improvement strategy	S15
39	Artificial intelligence-based solutions for climate change: a review	S16
37	Data-driven probabilistic machine learning in sustainable smart energy/smart energy systems: key developments, challenges, and future research opportunities in the context of smart grid paradigm	S17
44	Intelligent energy management: evolving developments, current challenges, and research directions for sustainable future	S18
40	Intelligent systems for building energy and occupant comfort optimization: a state of the art review and recommendations	S19
37	Optimizing the energy consumption in a residential building at different climate zones: Towards sustainable decision making	S20
38	A review on international ecological legislation on energy consumption: greenhouse gas emission management	S21
35	Identifying and analyzing the cultural, social and technical components of optimizing electricity consumption in the residential sector (case of study: the area covered by Fars Regional Electricity Company).	S22
45	Investigating the factors affecting energy consumption in Iran (with an emphasis on the variable of financial development)	S23
33	Energy consumption management capacities in Iran in the horizon of 1420: comprehensive modeling approach of energy supply and demand.	S24
39	Renewable and non-renewable energy, regime type and economic growth,	S25
35	Modeling UK natural gas prices when gas prices periodically decouple from the oil price.	S26
33	electricity demand through smart metering: The role of improved information about Reducing household energy saving	S27

The fifth step of analysis and integration of qualitative findings: the goal of the meta-combination method is to create a unified and new interpretation of the findings. In this step, qualitative findings were analyzed and integrated. The main process used in this stage was that first all the factors extracted from the articles were considered as codes, and then by placing similar codes in a category of components and finally, similar components within the categories, the work of analyzing and combining the findings was completed.

Table 3. Main codes and categories

Main categories	Codes
Financial arrangements	• Financial development Stock • Market Development Credit • Market Development

	• Development of the whole financial markets • The use of long-term financing in the gas industry • Low interest loans from banks
Use of renewable energy	• Use of renewable energy • Replacement of electric energy produced by renewable energy • Production of various renewable energy sources (wind, sun, water and geothermal) in the long term • Renewable production • Replacing fossil energies with renewable ones • Reducing the total consumption of petroleum products and natural gas
Technology	• Technology development in industry • Solar energy technology • Wind energy technology • Water gas technology
Investment development	• Private sector investment in renewable energies • Investment priority in this industry • Increase domestic investment • Advice on investment for production
Government support policies	• Fiscal policies to reduce greenhouse gas emissions • Integrating the environmental law system for all organizations
Creating national income	• Increase in national income • Trade liberalization • Economic Growth
Existing shortcomings	• Weakness of individual responsibility • Low technical knowledge and awareness • Lack of technological developments • Absence of energy policies on methods of action • Unstable energy consumption • Continuity of energy consumption in the form of consumption habits in families • The existence of technical and technological problems in optimizing the energy of industrial customers • Using worn out and ineffective equipment
Existing obstacles	• Policy/legal barriers • Management barriers • Financial barriers • Information/data barriers • Cultural/organizational barriers • Technical barriers
Cultivation of subscribers	• Economic-social base of households, • Culture (environment) of households • Addressing the need to optimize energy consumption at the national level
Provide optimal services	• Achieving quality services at minimal cost • Optimal consumption in service and household sectors

The sixth step of quality control

Neutral coding method was used to check the accuracy of the done coding. In this method, a person who has no mental background of the research subject is asked to check and recode the text of the interviews.

For this purpose, the implemented text of the interviews was presented to a PhD researcher who was asked to code them based on his perception. In the end, in order to check the agreement between two codings, Kappa coefficient was calculated using SPSS software. If this coefficient is higher than 0.6 in meaningful conditions, it is good, and if it is more than 0.75, it indicates an excellent agreement between the coders. At this stage, kappa of 0.88 was obtained.

The seventh step of presenting the findings

In this step, a summary of the grouping of dimensions and components extracted from the research literature is shown. For this purpose, according to the purpose of the research, an expert panel was formed and a group of experts in the field of gas industry, including managers, supervisors, experts, university professors who had experience and practical records in this field, were asked to review the extracted factors and groupings and give their final opinions. express to reach a consensus. Therefore, in the first step, the decision matrix is formed. The points obtained from the decision matrix regarding the issue are presented in the following table:

Table 4. Determining the importance and emphasis of past researches

Rank	Importance factor Wj	Uncertainty Ej	$\sum P_{ij} \times knP_{ij}$	Frequency	Code
2	0.14487	0.695459	-0.31652	9	Use of renewable energy
4	0.109103	0.52376	-0.23837	5	Gas consumption management
1	0.168354	0.808199	-0.36783	17	Shortcomings
5	0.095975	0.460735	-0.20969	4	obstacles
6	0.080386	0.385898	-0.17563	3	Data driven solutions
6	0.080386	0.385898	-0.17563	3	Implications of gas consumption management
3	0.120271	0.577371	-0.26277	6	Economic Growth

A data-oriented model of gas consumption management with emphasis on the problem of unauthorized use is considered based on the analysis of information systems, in which factors such as the use of renewable energy, gas consumption management, shortcomings, obstacles, data-oriented solutions, The consequences of gas consumption management and economic growth should be used to maximize profitability and minimize costs. This research is simulated in MATLAB software. We consider the following general assumptions: 1) gas consumption is optimally structured, 2) gas organization components follow an independent Poisson flow, 3) each energy consumption optimization has only one base with exponential service times, and 4) There is an upper limit on maximum profitability and productivity.

To model this situation, we establish the following symbols:

- $M=\{1,2,\ldots,m\}$:The set of model component nodes
- $N=\{1,2,\ldots,n\}$:A set of gas consumption optimization nodes
- $D=(d_{ij})$:The distance matrix of the component node i to the gas consumption optimization node j
- Λ :The overall productivity rate of the optimization model
- λ_i :The rate of effective measures of gas consumption optimization $i \in M$
- γ_j :The rate of measures to optimize gas consumption $j \in N$
- μ :Average rate of actions in gas consumption optimization
- $W_j=(\mu-\gamma_j)^{-1}$:The waiting time of $j \in N$ the action that is assigned to the facilitation node
- $\overline{W}$:The upper limit of the allowed waiting time for actions taken to optimize gas consumption
- $v=1/\overline{W}$:Excess productivity capacity to guarantee $W_j \le \overline{W}$
- p :the number of efficiencies that actually led to profitability;
- $\overline{p}$:the maximum number of productivity that can be profitable;

This issue can be stated as follows:

Consider the following assumptions: a set of effective measures of gas consumption optimization denoted by λ_i, a set of average rates of measures in gas consumption optimization μ, a positive integer and a positive number $\overline{W}$; It specifies a set of gas optimizations that are maximally sized to minimize the average total number of actions that lead to the closest efficiency and wait there. Also consider the condition that the average waiting time in each optimization of gas consumption does not lead to the reduction of unauthorized use of $\overline{W}$

If, υ the speed of actions and

$$y_j = \begin{cases} 1 & \text{If a productivity is opened at node j؛} \\ 0 & \text{otherwise;} \end{cases}$$

$$x_{ij} = \begin{cases} 1 & \text{If action i leads to productivity j;} \\ 0 & \text{otherwise;} \end{cases}$$

Therefore, the cumulative action time of the components per time unit is equal to:

$$T = \sum_{i \in M} \sum_{j \in N} \lambda_i d_{ij} x_{ij} / \upsilon$$

Hence, each productivity behaves as an M/M/1 queue, the average waiting time at productivity location j is equal to $W_j = 1/(\mu - \gamma_j)$. Therefore, the cumulative $\gamma_j = \sum_{i \in M} \lambda_i x_{ij}$ action time of the components per time unit is equal to:

$$V = \sum_{i \in M} \sum_{j \in N} \lambda_i x_{ij} W_j = \sum_{j \in N} \frac{\gamma_j}{\mu - \gamma_j}$$

According to Little's law described in the previous sections, T represents the average number of actions being performed and V represents the average number of pending actions.

One of the system evaluation criteria is the percentage of time the system works. To show this standard, a factor called productivity or efficiency coefficient is used, which is defined as follows:

$$\rho = \frac{\text{The average of all actions to receive the service per unit of time}}{\text{The total capacity of the system for productivity per unit of time}}$$

According to this definition, the larger the value ρ, the greater the demand and the system has to do more work and the queue will be longer. On the contrary, the smaller it is, the shorter the time ρ, but on the other hand, less system facilities are used.

Now, in order to measure the average efficiency coefficient of the model in our model, we must first calculate the total efficiency coefficient of the facilities and divide it by the number of optimizations that have become profitable:

$$\frac{\sum_{i \in M} \sum_{j \in N} \lambda_i x_{ij}}{p\mu}$$

Or in other words:

$$\frac{\sum_{i \in M} \sum_{j \in N} \lambda_i x_{ij}}{\sum_{j \in N} \mu}$$

To ensure that actions move to the nearest point of profitable productivity, we need to:

$$\sum d_{ik} x_{ik} \le (d_{ij} - \Delta) y_j + \Delta, \qquad \forall i \in M, j \in N,$$

Therefore, we obtain the following mathematical programming formulation:

(1) $$\min \sum_{i \in M} \sum_{j \in N} \frac{\lambda_i d_{ij} x_{ij}}{\upsilon}$$

(2) $$\min \sum_{i \in M} \sum_{j \in N} \frac{\lambda_i x_{ij}}{\mu - \sum_{k \in M} \lambda_k x_{kj}}$$

(3) $$\max \frac{\sum_{i \in M} \sum_{j \in N} \lambda_i x_{ij}}{\sum_{j \in N} \mu}$$

(4) $$subject\ to \qquad \sum y_j \le \bar{p},$$

(5) $$\sum_{j \in N} x_{ij} = 1, \qquad \forall i \in M,$$

(6)

(7) $$x_{ij} \le y_j, \qquad \forall i \in M, j \in N,$$

(8) $$\sum_{k \in N} d_{ik} x_{ik} \le (d_{ij} - \Delta) y_j + \Delta, \qquad \forall i \in M, j \in N,$$

$$\sum_{i \in M} \lambda_i x_{ij} \le \mu - v, \qquad \forall i \in M, j \in N$$

$$y_j \in \{0,1\}, \quad x_{ij} \in \{0,1\} \qquad \forall i \in M, j \in N$$

Objective (1) represents the minimization of the average number of ongoing actions, goal (2) represents the minimization of the average number of pending actions, and goal (3) represents the maximization of the total gas consumption optimization function per unit of time. These goals are according to the limitations that have been stated, that limitation (4) refers to the maximum amount of optimization of gas consumption that may be profitable. Constraints (5) and (6) guarantee that each action request achieves gas consumption optimization, and this action ends only in a profitable gas consumption optimization. Constraint (7) also guarantees that this action is carried out to the closest optimization of gas consumption. At the end of constraint (8), it guarantees that the average waiting time in each optimization of gas consumption does not exceed

In terms of scheduling, the problems were categorized based on the number of tasks or N (10, 20, 30, 40, 50, 100, and 200 tasks) and the number of machines or M (5, 10, 15, and 20 machines). As a result, a total of twenty-eight groups were selected, and 10 cases were randomly created in each group. Processing and adjustment times were selected from uniform distribution functions between 1 and 19 and between 1 and 9 (U(1,19) and U(1,99)), respectively. The total finishing time was considered as a fitting function and the PM index was used to evaluate the answers as follows:

$$PM = \frac{Heu_{sol} - Best_{sol}}{Best_{sol}}$$

In which, the total finishing time obtained by a specific method with Heusol and the best answer among the three methods are displayed with Bestsol. All algorithms were coded with MATLAB. Due to the probabilistic nature of evolutionary algorithms, the standard approach in comparing them is to repeat the execution of each case several times. Due to the existence of the same comparison conditions, all three algorithms were executed ten times for each group, and the stopping criterion for all three algorithms was assumed to be a fixed number of repetitions.

Table 4 shows the minimum, maximum and average PM for each method. Also, the average time to execute the algorithm (average of ten executions) is shown in the table. The subscript PM in the MIN column shows how many times the corresponding algorithm has reached the minimum (Bestsol) in 10 times of execution. According to Table 4, the NGA algorithm is the best algorithm based on the PM value, but the combined genetic algorithm (HGA) works a little faster.

Table 4. *PM value for three selected algorithms (times are in seconds)*

HACO				***HGA***				***NGA***				***M***	***N***	***Problem class***
Max PM	***Average***		***Min PM***	***Max PM***	***Average***		***Min PM***	***Max PM***	***Average***		***Min PM***			
	Time	***PM***			***Time***	***PM***			***Time***	***PM***				
0.19	1.96	0.21	2	0.01	1.83	0	4	0.13	1.05	0.06	5	5	10	1
0.16	2.77	0.18	2	0.14	1.84	0.08	3	0.1	1.21	0.05	5	10	10	2
0.21	5.53	0.04	0.01	0.01	2.78	0.01	5	0.11	2.39	0.05	5	15	10	3
0.08	8.28	0.09	2	0.05	4.01	0.03	3	0.09	5.11	0.03	6	20	10	4
0	2.44	0	1	0.02	2.15	0.01	2	0	1.55	0	7	5	20	5
0.1	4.79	0.11	2	0.17	2.77	0.09	3	0.1	1.76	0.01	9	10	20	6
0.07	9.56	0.01	0	0.06	2.94	0.03	4	0.16	3.86	0.02	9	15	20	7
0.24	13.31	0.3	1	0.17	5.05	0.07	5	0.05	6.87	0.02	6	20	20	8
0.16	3.43	0.2	1	0.13	2.76	0.09	3	0.13	1.77	0.05	6	5	30	9
0.19	6.85	0.23	1	0.03	3.59	0.02	3	0.14	3.22	0.02	9	10	30	10
0.03	9.25	0.02	0.01	0.02	4.34	0.02	2	0.01	4.48	0	9	15	30	11
0.21	13.53	0.04	0.01	0.1	6.1	0.04	5	0.01	7	0	8	20	30	12
0.21	3.4	0.23	2	0.11	3.24	0.06	4	0.09	2.2	0.04	5	5	40	13
0.17	6.62	0.03	0.01	0.13	4.29	0.1	4	0.18	2.86	0.07	6	10	40	14
0.21	8.11	0.03	0	0.18	5.61	0.1	4	0	4.37	0	6	15	40	15
0.26	15.62	0.04	0.01	0.01	7.83	0.01	3	0.08	9.41	0.03	7	20	40	16
0.03	3.4	0.04	2	0.17	3.87	0.11	3	0.1	2.92	0.03	7	5	50	17
0.17	6.63	0.03	0	0.02	5.11	0.01	4	0.09	5.47	0.03	7	10	50	18
0.26	10.84	0.03	0	0.04	7.04	0.02	4	0.05	8.94	0.02	6	15	50	19
0.2	14.86	0.03	0	0	10.89	0	5	0.15	11.15	0.08	5	20	50	20
0.15	5.96	0.19	1	0.08	6.14	0.03	5	0.17	4.5	0.03	8	5	100	21

0.21	19.22	0.02	0	0.08	13.22	0.03	5	0.1	9.64	0.05	5	10	100	22
0.17	22.94	0.04	0.01	0.13	18.59	0.07	3	0.13	15.38	0.04	7	15	100	23
0.09	32.28	0.11	1	0.01	27.49	0.01	3	0.01	28.27	0.01	6	20	100	24
0.03	13.66	0.02	0	0.08	14.55	0.04	4	0.06	11.22	0.01	9	5	200	25
0.26	27.74	0.04	0.01	0.13	26.79	0.06	4	0.07	32.54	0.03	6	10	200	26
0.27	38.28	0.04	0.01	0.15	32.15	0.05	5	0	37.36	0	6	15	200	27
0.14	97.6	0.15	2	0.14	73.32	0.1	2	0.07	75.78	0.01	9	20	200	28

Overall, simulating gas energy consumption management using a genetic algorithm can provide efficient and effective solutions, handle complex and dynamic scenarios, and offer insights into optimizing gas consumption and energy efficiency.

5. Discussion

Based on the results obtained in the meta-combination technique, the main categories are: use of renewable energy, gas consumption management, shortcomings, obstacles, data-driven solutions, consequences of gas consumption management and economic growth. Financial arrangements have codes for financial development, stock market development, credit market development, development of the entire financial markets, use of long-term financing in the gas industry, low-interest loans from banks. Utilization of renewable energies with renewable energy usage codes, replacement of electric energy produced by renewable energies, production of various renewable energy sources (wind, sun, water and geothermal) in the long term, renewable production, replacement of fossil energies with renewable and Reducing the total consumption of petroleum products and natural gas. Technology and technology have the codes of technology development in industry, solar energy technology, wind energy technology and water gas technology.

Investment development with private sector investment codes in renewable energy, investment priority in this industry, increasing domestic investment and recommending investment for production, government policies with tax policy codes to reduce greenhouse gas emissions, integration. The environmental law system for all organizations, the creation of national income increases with national income codes, trade liberalization and economic growth. The existing deficiencies are coded as weak individual responsibility, low awareness and technical knowledge, lack of technological developments, lack of energy policies on working methods, unsustainable energy consumption, continuity of energy consumption in the form of wasteful consumption habits in families, existence of technical problems and It is technological in optimizing the energy of industrial subscribers and using worn out and inefficient equipment. Existing barriers are coded as Policy/Legal Barriers, Management Barriers, Financial Barriers, Information/Data Barriers, Cultural/Organizational Barriers, and Technical Barriers. Cultivation of subscribers has the codes of economic-social base of households, (environmental) culture of households and addressing the need to optimize energy consumption at the national level. Providing optimal services has codes to improve the ability to provide services and satisfy customers. Kaur (2023), energy analysis requires data mining techniques that can incorporate unknown complex interactions and nonlinearities in systems. Karkacier et al. (2005) determined the input and output factors to optimize gas consumption as in the present study. Fazal et al. (2018) considered technical and qualitative factors necessary to create an energy consumption management optimization model.

6. Conclusion

Many industrialized countries and developing countries have implemented policies and mechanisms in the field of energy conservation and saving in the face of the energy crisis for many years. Also, the executive actions both at the national and regional level and at the international level have been placed on the agenda of these countries. In general, in these countries, policies and mechanisms in various fields of transportation, industries, construction and household appliances, and energy production methods have been comprehensively implemented and by improving them, they have been able to use more effective methods to save energy in appropriate ways for Save energy and reduce environmental damage. The use of data analysis in the management of gas energy consumption can help to improve system efficiency, identify weaknesses and losses, increase productivity and optimize the use of gas energy.

Simulating gas energy consumption management based on a genetic algorithm offers several advantages. Here are some of the key advantages:

Genetic algorithms are optimization techniques that can effectively search for optimal or near-optimal solutions in complex problem spaces. By simulating gas energy consumption management using a genetic algorithm, you can find optimal strategies for managing gas consumption, maximizing energy efficiency, or minimizing costs.

Flexibility: Genetic algorithms are flexible and can handle a wide range of problem types and constraints. They can accommodate different objective functions, multiple constraints, and nonlinear relationships, making them suitable for modeling and optimizing gas energy consumption management, which involves various factors and complexities.

Genetic algorithms have the ability to adapt and evolve over iterations. They maintain a population of candidate solutions and use crossover and mutation operators to generate new solutions. This allows them to explore different regions of the solution space and adapt to changing conditions or constraints, making them suitable for dynamic gas energy consumption management scenarios.

Genetic algorithms are inherently parallelizable, which means they can take advantage of parallel processing architectures and distribute the computation across multiple cores or machines. This enables faster convergence and the ability to handle larger problem instances, making them efficient for simulating and optimizing gas energy consumption management.

Genetic algorithms are robust optimization techniques that can handle noisy or incomplete data. They are less prone to getting trapped in local optima compared to traditional optimization methods. This robustness makes them suitable for gas energy consumption management, where data uncertainty and variability are common.

Genetic algorithms allow for exploratory analysis by generating diverse solutions. They can provide insights into the trade-offs and relationships between different variables and objectives in gas energy consumption management. This can help decision-makers understand the sensitivity of their strategies and make informed decisions.

Based on the analysis, it was shown that data mining can be very useful in managing gas energy consumption and identifying unauthorized branches. Below are some suggestions based on the results obtained:

-By using data mining, it is possible to identify gas energy consumption patterns and suggest improvements in energy consumption. Based on the patterns, recommendations can be made to optimize consumption, such as best usage times, temperature and pressure control, system efficiency, and other related factors.

-By analyzing gas consumption data, unusual and suspicious patterns can be identified and unauthorized branches can be identified. These patterns can include sudden and unusual consumption, patterns different from usual consumption, sudden changes in consumption and other suspicious patterns. Using data mining, a warning system can be implemented to identify unauthorized branches. This system can issue alerts based on certain patterns and indicators extracted from the data and activate the necessary measures to investigate and control suspicious branches. By analyzing data on gas consumption and related environmental factors, it is possible to identify system components where more energy losses occur. This analysis can be used to improve the gas distribution system and increase efficiency, such as detecting leaking lines or analyzing consumption in certain parts of the distribution network. By using data mining, it is possible to predict the future consumption and make proper planning for gas production, distribution and storage. This prediction can be done using prediction algorithms such as linear methods, neural networks and other existing methods.

To improve gas consumption management, based on the proposed model, the following are provided:

-Launch educational programs to increase awareness and educate consumers about the correct ways to use natural gas and reduce energy waste. These trainings can include instructions on correct thermostat setting, proper insulation of the building, use of energy-efficient equipment, and promotion of awareness about the benefits of reducing gas consumption.

-Encouraging the use of better and less energy-efficient equipment such as smart thermostats, high-efficiency boilers, and advanced heating and cooling systems that reduce energy losses. Also, the improvement of network systems for intelligent management of demand and gas supply can help to increase efficiency and reduce energy consumption.

-Providing facilities and financial discounts to individuals and organizations to make energy improvements in domestic and industrial heating and cooling systems. This includes loan facilities, financial discounts for the purchase of energy-efficient equipment, and support for the installation of renewable production systems.

-Using intelligent energy management and Internet of Things technologies to control and optimize gas consumption. This includes the use of automatic and intelligent systems to control the temperature and schedule the use of gas in heating and cooling systems.

-Promoting the use of clean and compressed natural gas, using renewable electricity generation systems such as solar cells and wind turbines, and supporting research and development projects in the fields of renewable energy.

-Research and development projects for exploiting the heat produced in industrial processes and using it for heating spaces and drinking water.

- Establish surveys and performance indicators to evaluate and monitor gas consumption in organizations and industries, and provide feedback and guidance for continuous performance improvement.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Reference

Adams, S. Klobodu, E. Apio, A. (2018). Renewable and non-renewable energy, regime type and economic growth, *Renewable Energy*, 125, 755-767.

Aghai, M., Qolizadeh, R., & Abdi, Y. (2018). Financial development and technology development of renewable energies in different sectors: an application of Tobit panel model. *Economic Research*, 54, 284-253. in Persian]

Ahmad, T., Madonski, R., Zhang, D., Huang, C., & Mujeeb, A. (2022). Data-driven probabilistic machine learning in sustainable smart energy/smart energy systems: Key developments, challenges, and future research opportunities in the context of smart grid paradigm. *Renewable and Sustainable Energy Reviews*, *160*, 112128.

Akbari, M., Asghari, M., Emami, A., Davari, P., Salamat Sani, S., Taherian, N. & Qolinejad, M. (2022). Presenting a model for predicting household gas consumption with the help of air temperature and number of subscribers. *New applied and computational findings in mechanical systems*, 2, 60-68. [in Persian]

Akyol, M., & Uçar, E. (2021). Carbon footprint forecasting using time series data mining methods: the case of Turkey. *Environmental Science and Pollution Research*, *28*, 38552-38562. https://doi.org/10.1007/s11356-021-13431-6

Ali, M., Prakash, K., Hossain, M. A., & Pota, H. R. (2021). Intelligent energy management: Evolving developments, current challenges, and research directions for sustainable future. *Journal of Cleaner Production*, *314*, 127904.

Asadi, A. (2018). Investigating factors affecting energy consumption in Iran (with emphasis on financial development variable). *Financial and Economic Policy Quarterly*, 7, 151-177. [in Persian]

Asche, F. Oglend, A., & Osmundsen, P. (2017). Modeling UK natural gas prices when gas prices periodically decouple from the oil price. *The Energy Journal*, *38*(2): 1-20.

Boodi, A., Beddiar, K., Benamour, M., Amirat, Y., & Benbouzid, M. (2018). Intelligent systems for building energy and occupant comfort optimization: A state of the art review and recommendations. *Energies*, *11*(10), 2604.

Carroll, J., Lyons, S., & Denny, E. (2014). Reducing household electricity demand through smart metering: The role of improved information about energy saving. *Energy Economics*, *45*, 234-243.

Chen, L., Chen, Z., Zhang, Y. et al. (2023). Artificial intelligence-based solutions for climate change: a review. Environ Chem Lett. https://doi.org/10.1007/s10311-023-01617-y

Fazal, R., Rehman, S. A. U., Bhatti, M. I., Rehman, A. U., Arooj, F., & Hayat, U. (2021). A Cross-Sectoral Investigation of the Energy–Environment–Economy Causal Nexus in Pakistan: Policy Suggestions for Improved Energy Management. *Energies*, *14*(17), 5495.

Gao, F., & Shao, X. (2021). Forecasting annual natural gas consumption via the application of a novel hybrid model. *Environmental Science and Pollution Research*, *28*, 21411-21424. https://doi.org/10.1007/s11356-020-12275-w

Houshang, A. (2016). *Investigating the solutions to prevent manipulation and theft of gas in the gas companies of East Azarbaijan province*. 82-84. [in Persian]

Karkacier, O., & Goktolga, Z. G. (2005). Input–output analysis of energy use in agriculture. *Energy Conversion and Management*, *46*(9-10), 1513-1521.

Kaur, K. (2023). Artificial Neural Network Model to Forecast Energy Consumption in Wheat Production in India. *Journal of Statistical Theory and Applications*, 1-19. DOI: 10.1007/s44199-023-00052-w

Liu, S. H., Sun, W. Q., Li, W. D., & Jin, B. Z. (2023). Prediction of blast furnace gas generation based on data quality improvement strategy. *Journal of Iron and Steel Research International*, 1-11. https://doi.org/10.1007/s42243-023-00944-2

Liu, W., Zhao, J., & Wang, D. (2021). Data mining for energy systems: Review and prospect. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *11*(4), e1406. DOI: 10.1002/widm.1406

Mischos, S., Dalagdi, E., & Vrakas, D. (2023). Intelligent energy management systems: a review. *Artificial Intelligence Review*, 1-40. https://doi.org/10.1007/s10462-023-10441-3

Mohammadi, T., Ghasemi, A., & Nekunam, A. (2017). The reaction of natural gas price to crude oil price changes in the regional market of Europe and Asia: Markov vector regime approach. *Iranian Energy Economics Research Journal*, 7(27), 1-30. [in Persian]

Pertoi Sangi, M., Momenzadeh Haghighi, H., & Arfainia, H. (2018). *Prediction of customers' gas consumption using data mining in Bushehr Gas Company, 6th National Conference of Computer Science and Engineering and Information Technology*, Babol. [in Persian]

Pouriani, A., Mehzani, H., Samii, R., Shujaei, S., & Omidkhah Nasrin, M. (2019). Compilation of turning scenarios of natural gas consumers (case study: Mazandaran Gas Company). *Iranian future research*, 5, 229-251. [in Persian]

Qashou, A., Yousef, S., & Sanchez-Velazquez, E. (2022). Mining sensor data in a smart environment: a study of control algorithms and microgrid testbed for temporal forecasting and patterns of failure. *International Journal of System Assurance Engineering and Management*, *13*(5), 2371-2390. https://doi.org/10.1007/s13198-022-01649-7

Qiang, G. Liu, X. Zeng, Y. Han, S. (2022). An energy efficiency solution based on time series data mining algorithm on elementary school building, *International Journal of*

Low-Carbon Technologies, 17, 356–372. DOI: 10.1093/ijlct/ctac008

Quaid, A. Dehghani, A. Fatahi, M. (2018). Investigating the impact of different types of renewable energy sources on Iran's economic growth. Management, *Economics and Accounting*, 35, 148-137. [in Persian]

Rahimi, F., Kamranrad, R., & Zarei, A. (2022). Design of integrated clustering-association data mining model to study the electricity consumption behavior of industrial units. *Iranian Journal of Energy*, *25*(3), 65-78.

Selimian, Z., Gudarzi Rad, R., Badaghi, M., Makarizadeh, V. Farmed, M., & Shafizadeh, M. (2020), Energy consumption management capacities in Iran in the horizon of 1420: comprehensive modeling approach of energy supply and demand. *Quarterly Journal of Energy Planning and Policy Research*, 7, 51-85. [in Persian]

Sharma, K., Dwivedi, Y. K., & Metri, B. (2022). Incorporating causality in energy consumption forecasting using deep neural networks. *Annals of Operations Research*, 1-36. https://doi.org/10.1007/s10479-022-04857-3

Tam, V. W., Le, K. N., Tran, C. N., & Illankoon, I. C. S. (2021). A review on international ecological legislation on energy consumption: greenhouse gas emission management. *International Journal of Construction Management*, *21*(6), 631-647.

Tushar, Q., Bhuiyan, M., Sandanayake, M., & Zhang, G. (2019). Optimizing the energy consumption in a residential building at different climate zones: Towards sustainable decision making. *Journal of cleaner production*, *233*, 634-649.

Vali, M., Salimifard, K., Gandomi, A. H., & Chaussalet, T. J. (2022). Care process optimization in a cardiovascular hospital: an integration of simulation–optimization and data mining. *Annals of Operations Research*, *318*(1), 685-712. https://doi.org/10.1007/s10479-022-04831-z

Varlamis, I., Sardianos, C., Chronis, C., Dimitrakopoulos, G., Himeur, Y., Alsalemi, A., ... & Amira, A. (2022). Smart fusion of sensor data and human feedback for personalized energy-saving recommendations. *Applied Energy*, *305*, 117775.

Wu, P. Wang, Y. Jiang, C. (2023). Dynamic slack-based measure model efficiency evaluation of the impact of coal mining characteristics. *Energy Efficiency*, 16, 11. https://doi.org/10.1007/s12053-023-10085-w

Yazdan Panahfard, S., Heydari, A., & Gurbanpour, A. (2019). Recognition and analysis of cultural, social, and technical components of optimization of electric energy consumption in the residential sector (case of study: an area covered by Fars Regional Electric Company). *Quarterly of Applied Economic Theory*, 4, 85-116. [in Persian]

Zabihi, Z. (2016). *Investigating the unauthorized branches turned into authorized ones by the private sector and the impact of the revenues on the economy of the water and sewage company (a case study of the unauthorized branches of Yasouj city)*. The first national conference on water consumption and waste management, 1-9. [in Persian]

Zhou, J., Lin, H., Jin, H., Li, S., Yan, Z., & Huang, S. (2022). Cooperative prediction method of gas emission from mining face based on feature selection and machine learning. *International Journal of Coal Science & Technology*, *9*(1), 51. https://doi.org/10.1007/s40789-022-00519-8