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Research Article

A Novel Framework for Sustainable Hybrid Energy Distribution Network Using Distributed Decision Protocols

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Abstract
Nowadays, population growth and technological advancements are contributing to the growth of global electricity demand. The aim of this research is to form a new distributed decision-making protocol (DDM) to increase the reliability and sustainability of HES. Using this DDM, it is intended to minimize the effects of planned and unplanned production interruptions on the independent and autonomous energy producers within the HES. The novelty of this study lies in the development of a decentralized decision-making protocol that enables autonomous energy producers within HES to collaboratively optimize resource utilization, enhance system resilience, and dynamically adapt to fluctuations in energy demand and supply without reliance on a central authority. By implementing this protocol, energy producers in the HES are intended to collaborate and achieve mutual benefits in cases where they are not able to fulfill the needs of their customers. As a case study, there are sixteen independent power plants that are simulated as CN enterprises in four independent communities. The DDM protocol aims to manage the collaboration among independent energy producers, to use the sources of the producers effectively, to increase the profit rates, and to optimize the sustainability of the energy supply for each community. The results demonstrates that the proposed protocol gives satisfying results under the criteria of profit, demand fulfillment rate, sustainability, and resource utilization both for each energy producers and entire HES. Moreover, the increase in collaboration rate within each community increased these parameters by average of 90%.

Keywords
Distributed decision-making, Decentralized optimization, Systems analysis, Hybrid energy systems

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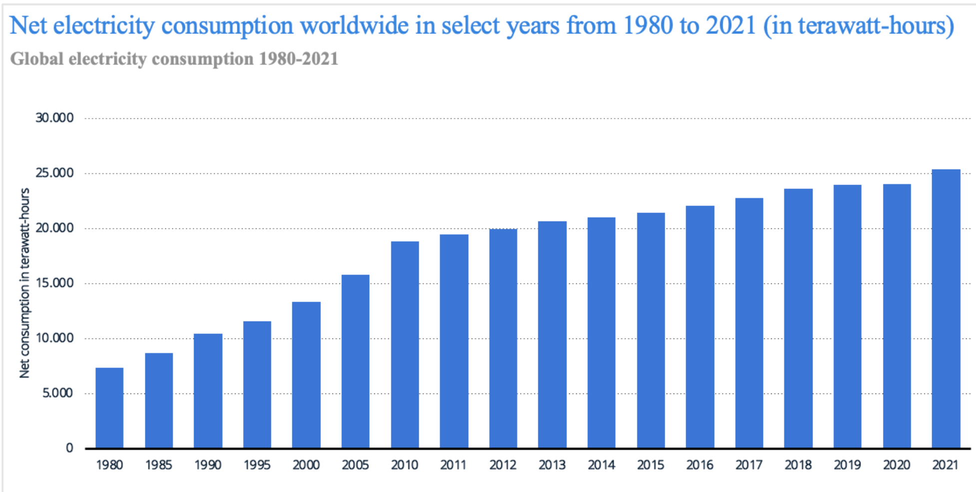
1. Introduction

Global electricity demand is growing each year due to population growth and technological developments for decades. With the worldwide population increasing by 27% the electricity consumption has gone up over the years since 1980 which is seen clearly in Figure 1. During the Covid-19 pandemic, countries faced strong decreases in electricity demand (Kumar et al., 2023)(Wu et al., 2023). Moreover, after the beginning of 2021, the recovery from the pandemic started, and the electricity demand has started to increase again as shown in Figure 1. Additionally, it is clearly seen in Figure 1. that the forecast of energy need in worldwide rises. With the increase in the population and technological deployments, it is estimated that the world's energy need will improve in the next 30 years, and its distribution according to different energy sources is demonstrated in Figure 1.

a



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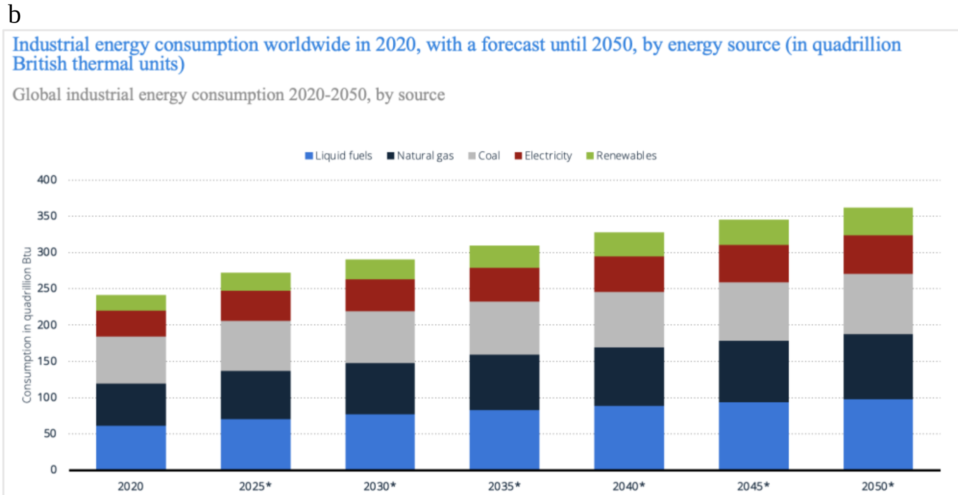

Figure 1. Electricity Consumption **(a)** Net Electricity Consumption Worldwide in Select Years From 1980 to 2021, www.statista.com, Source ID: 280704; **(b)** The Forecast of Industrial Energy Consumption Worldwide by Energy Sources Until 2050, www.statista.com, Source ID: 263471.

Countries try to satisfy the electricity demand from two types of energy sources which are conventional and renewable energy. The conventional energy industry relies on fossil fuels, such as oil, coal, and natural gas. Products derived from fossil fuels have detrimental effects on the environment and human health. In addition, it is unknown when the fossil-driven products are going to be depleted (J. Li, 2023). Currently, renewable energy sources consist of solar energy, wind energy, hydropower, geothermal power, and biomass power.

In energy utilization systems, solar and wind energy are the most frequently preferred renewable energy sources. The use of solar and wind energy is getting attractive due to the increasing importance of environmental concerns and getting less investment cost (Reddy, 2017). Renewable energy systems are used in industrial, agricultural, and household applications that require a continuous supply of electricity. There are number of applications available to provide sustainable and reliable energy supplies, including hybrid energy systems (HES).

As the renewable energy markets have progressed, the relevance of combining multiple power sources has grown in popularity. By using HES, we can overcome the limitations associated with individual production technologies in terms of efficiency, profitability, dependability, and flexibility. Moreover, HES reasonably higher quality of power output (Ghofrani & Hosseini, 2016). Regarding the stochastic nature of energy generation and distribution, there are both controllable and uncontrollable factors to consider.

Power plant failures or planned maintenance activities are controllable reasons, while environmental factors, arbitrary patterns of capacity and demand fluctuations are uncontrollable. Additionally, the stochastic nature of the weather conditions that affect electricity generation as well as system interruptions and malfunctions. Performance and failure rates of energy production are affected by such conditions. It is possible to minimize uncertainties and variations in energy production by designing HES that incorporates a variety of renewable or nonrenewable energy sources.

Decision-makers should consider the concerns: 1) how much energy could be produced and 2) how much demand could be satisfied. To manage hourly or certain period output of solar power or wind power flows has led to many studies in the literature. These studies have the objective of minimizing investment costs, providing an optimization algorithm, and minimizing system losses and total operating costs. There have been numerous studies to overcome such problems to reduce the uncertainties in energy generation forecasts (Syama & Ramprabhakar, 2022)(Al-Abri & Okedu, 2023). However, the ineffective utilization of renewable energy sources has caused many problems like both unsatisfied demand and excess capacity. By managing HES effectively, such uncertainties and variations can be mitigated.

There are two types of HESs: standalone and grid connected. It is referred to as HRES if two or more energy sources provide power to the grid. However, the common problems such as climate changes and unpredictable nature events for solar and wind energy systems, could not be eliminated (Mahesh & Sandhu, 2015). In addition, renewable energy sources could not be parallel to demand rates such as wind source is frequently unrelated to load patterns, thus it is occasionally discarded when it is sufficient. On the other hand, solar energy is only accessible throughout the daytime. In this way, HERSs are more effective than systems utilizing only one energy source. For the HES system to maximize its economic and environmental benefits, it requires effective management.

So that ensuring effective HES system management, each power plant in the system should be viewed as autonomous and independent. Each power plant has unique characteristics or attributes that should be considered before deciding. Each plant must, however, not only provide energy for the area of responsibility in a community but also help fulfill the energy needs of the community. As a result, each power plant of the HES should be considered not only for its own needs but also for those of the community. An environment such as this increases the uncertainty of decisions in the management of HES.

Due to the uncertainties on decision problems, decision-makers face more complex problems that are hard to deal with. Therefore, the distributed decision-making (DDM) mechanism of complex problems addresses significant and rapidly rising in decision theory. Finding a solution for complex problems could not be possible or applicable with centralized decision-making methods. Therefore, DDM is getting the attention of decision-makers since DDM provides flexibility and autonomy to decision-makers. In contrast, centralized methods do not support autonomous and independent decision-making.

This paper aims to build HESs in harmony. Power plants are built in individual communities that are isolated from one another to fulfill the energy requirements of local customers, and which may have a variety of energy sources. Community based hybrid energy grids create networks through demand and capacity sharing decisions among power plants. To enhance the reliability and sustainability of Hybrid Energy Systems (HESs), a new Distributed Decision-Making (DDM) protocol is proposed, enabling decentralized coordination among power plants by optimizing energy distribution, balancing supply and demand in real time, and facilitating adaptive resource allocation based on the dynamic needs of individual communities, thereby ensuring efficient utilization of diverse energy sources while minimizing energy losses and enhancing overall system resilience. Moreover, the proposed demand-capacity sharing protocol has not been previously applied in hybrid energy systems, making this study a benchmark for demonstrating its potential effectiveness in optimizing energy distribution, enhancing sustainability, and improving the overall reliability of decentralized energy networks.

In this work, collaborative communities are assumed to share the excess demands and capacities with other collaborative communities by defined decision-making protocols. Through the decision-making process, collaborative communities achieve their goals. Meanwhile, each community can optimize its local objectives while the global network objective is succeeding with mutual benefits of the collaborating communities, regardless of demand and capacity patterns. To handle the arbitrary nature of communities' demands and dynamic changes of the generated energy, a new decision protocol is proposed by Demand and Capacity Sharing Protocol (DCSP) (Yoon & Nof, 2010a).

According to the literature, DCSPs are used to improve the efficiency of distributed decision problems. In distributed problems, decentralized and collection of limited knowledge source structure for such problem solvers does not promise reliability, speed, and tolerance to the uncertain data. As a result, the Contract Net Protocol (CNP) was designed as a high-level protocol for facilitating communication between nodes in a distributed system.

CNP proposed originally in Smith (Smith, 1980) and has been used for task allocation in distributed systems to connect between the manager agent and multiple contractor agents. Such as in a dynamic manufacturing system, CNP based scheduling scheme is proposed to maximize machine utilization and improve the performance of machine owing to interactive bidding process (Y. Wei et al., 2007). Multiple agent system is an important task allocation method that composes of the main idea of CNP. The collaborative network enterprises (CNE) formed designed and systemized relations. Moreover, during the collaboration of enterprises, the aim of enterprises is accomplished by interactions among them such as negotiation, decision-making processes, information sharing and coordination (C. Y. Huang & Wu, 2003).

Each enterprise faces the problem of demand uncertainty and inventory management. Collaboration between two or more enterprises creates an enterprise network. Therefore, collaboration strategy is applied in various applications of CNEs from production industry to service industry. For example, when a customer order of enterprise cannot be satisfied, the demand will be shared with other enterprises having excess capacity, and the remaining capacity of other enterprises could be reaching maximum utilization; therefore, mutual benefits of enterprises can be obtained. CNE is therefore considered to be an attractive strategy to achieve mutual benefits in terms of demand fulfillment rate, total profit, and capacity management. The coordination among the CNEs could be increased by distributed decision protocols (Ajidarma et al., 2022)(Yilmaz & Yoon, 2020).

This work proposes a distributed decision-making method for HESs. Also, it provides analyses and methods to prevent imbalanced situations between supply and demand of solar, wind, thermal and hydroelectric power plants. HESs has many random variables and factors which requires an optimization of components to achieve the economic, technical, and environmental objectives. For this purpose, a systematic solution methodology is observed by CNE approach.

This paper presents the one of the first implementation of CNE approach on the HES management. The proposed method has many advantages compared with centralized methods. Firstly, the capacity utilization rate of each energy sources is at least or more efficient and higher than the traditional centralized method. The decentralized methods enable method a more powerful use of limited resources and more flexible in meeting increasingly diverse demands due to having distributed decision-making.

Secondly, the unsatisfied demand rate and total cost are reduced. The cost will increase with the amount of capacity where the energy production to meet the demand cannot be realized, and meanwhile, the demand coverage ratio will decrease.

Thirdly, the proposed method provides efficient the usage of renewable power plants in terms of operating cost or power interruptions. The amount of energy produced by energy resources with the variability of nature and the planned or unplanned situations of energy resources are the reasons that prevent the effective use of energy resources. Therefore, the distributed decision model enables the efficient use of energy resources originating from its flexible structure. This research is based on the author's Ph.D. thesis which is titled as “Fuzzy decision protocol in collaborative network of enterprises” (Caglayan, 2024).

The sections of the study have been organized as follows: Section 2 explains literature review of HES management system, DDM approach and CNE methodology; Section 3 explains the essences of DCSPs, the proposed decision-making protocol and problem environment. The experimental results and analysis are presented in Section 4. Finally, Section 5 concludes this research with conclusions and future work directions.

Symbols and Abbreviations

DDM	*Distributed Decision-Making Protocol*
HES	*Hybrid Energy Systems*
DCSP	*Demand And Capacity Sharing Protocol*
CNP	*Contract Net Protocol*
CNE	*Collaborative Network Enterprises*

2. Literature Review

As the world’s population grows and technology advances, the demand for energy increases every day. Fossil fuels are one of the most widely used energy sources. However, the CO2 produced by burning of the fossil fuels harms the environment. Therefore, fossil fuel is one of the main actors of global warming. Renewable energy sources are the solution to the global energy crisis. In nature, there are different types of energy obtained from the energy flow that exists in natural processes such as wind, solar, geothermal.
Twenty percent of the world’s energy demand is met by renewable energy in at least twenty countries (Kumar et al., 2023). Moreover, national renewable markets forecast to continue to grow strongly in the next decade and beyond (*Global Futures Report - REN21*, n.d.). Therefore, there have been different studies to increase the efficiency of renewable energy systems. The balance between demand and capacity is the main element. Additionally, balance between energy output and demand could not be achieved due to factors such as weather conditions, fluctuating demand, and the failure of energy sources. Forecasting demand, having adequate capacity to meet demand, and effectively using available capacity are therefore important topics in the energy sector. Some of these problems have been mentioned in the literature.

Demand management and forecasting future energy requirements have increased exponentially in recent years because of the increasing use of renewable energy. For this reason, various forecasting models has been used for energy demand such as time series, integrated models, regression, swarm optimization, genetic algorithm (Suganthi & Samuel, 2012).
Wind and solar energy systems are extremely popular due to their environmental friendliness and cost-effectiveness. Solar energy is the one of best renewable energy sources on the environment. Because in the long-term issues it is freely available, and as a result accessibility, capacity utilization and efficiency are higher (Kannan & Vakeesan, 2016). Another study shows that global energy demand can be met satisfactorily, as solar energy is abundant in nature and is a freely available source of energy (Lewis, 2007).
The most used renewable energy source is wind energy, which involves the conversion of wind energy into useful energy forms, such as electrical power or mechanical power, by using wind turbines. The wind turbines are built to use wind power. Meteorological conditions and topographic structure have an important effect on the intensity and other characteristics of the wind in a region. Therefore, the energy output of the energy system is influenced by the performance and failure rates of the wind turbines. For example, according to study in 2010 in all over the world the total power was 194,400 MW (Minowa et al., 2012).
Developing a forecast of the wind farm's energy output and demand is a significant complexity due to the nature of the weather and the location of wind turbine failures. Therefore, there have been various study in the literature (Al-Abri & Okedu, 2023)(Al-khaykan et al., 2023). According to the study by using local weather data and Scientific Measurement and Evaluation Program (WMEP) wind tribune failures and weather conditions are analyzed and cross correlated (Tavner et al., 2010). When the monthly data is aggregated for various sites, the cross correlation between failure data and weather is between %55 and %75.
The uncertainty of wind and sun energy generation forecasts has been challenging due to fluctuations in seasonal, locational, environmental, and operational factors (Tavner et al., 2010). This paper enables to use of collaborative control theory to uncertainties of electricity capacity and demand. The weather conditions and output of wind turbines creates the fluctuation in electricity generation, and to handle with the difficulties energy collaboration distribution network is proposed by Jahanpour et al. (Jahanpour et al., 2016).
At first forecasting energy demand and predicting energy output second order regression model and multiple linear regression model are applied, and then DCSP and Best Matching Protocol (BMP) are proposed to obtain optimum profit of each community and get sustainable distribution network. As a result, variability of an excessive capacity and unfulfilled demand are increased approximately %85. Reducing the negative effect of these uncertainty condition, two CCT based protocols that are DCSP and BMP are suggested to create sustainable distribution network (Jahanpour et al., 2016).
In the literature hybrid energy system studies are also available (Al-khaykan et al., 2023)(Mertens, 2022). Hybrid energy systems are formed when two or more renewable energy sources, such as wind, solar, etc., are combined. Solar and wind energy are among the fastest growing energy sources within the renewable energy sources (IRENA, 2019). For the geographic information map of solar and wind hybrid energy sources assessment methodology has been studied by Ifaei (Ifaei et al., 2017). To meet the annual power demand for Iran, they proposed an algorithm-based data processing, optimization, clustering approach and sensitivity analysis. Due to the geographic conditions, higher investments in wind energy are not convenient. Due to the stochastic nature Syama and Ramprabhakar (Syama & Ramprabhakar, 2022) proposed a Long Short Term Memory model that is optimized by Bayesian optimization model for obtaining sustainable and effective HES. The result demonstrates that the proposed model has good forecast up to six hours added. As a case study, the wind and solar hybrid power availability of four different locations in Taiwan was analyzed (Shivam et al., 2020). The multi objective optimization is proposed by considering the feeding tariff regulation, environmental regulations in Taiwan. A planning method for DRL-MILP-based seasonal changes and multi-time scale WPHS-HES that will include different time periods of the day was developed, a model presented in this time was presented by Zang et al (H. Zhang et al., 2025).
The combined shared weighted short- term and long-term memory network combined with Gaussian process regression model is proposed to forecast energy demand due to uncertainties of hybrid energy system (H. Wei et al., 2019). Various scenarios of the uncertainties like the wind speed, solar radiation intensity was considered as input for the proposed optimal operation model. Yuan et al. (W. Yuan et al., 2021) proposed a stochastic optimization model to joint operation of PV and hydropower hybrid energy system to promote renewable energy consumption. For improving the solution efficiency various linearization approaches are suggested to model with different scenario-based MILP. A parallel swarm optimization algorithm is suggested to handle with uncertainties like growing environmental problems, and climate changes for sustainable hydro-wind-photovoltaic hybrid system (Zhu et al., 2020). Lu et al. (Lu et al., 2021) proposed a model for wind/ photovoltaic/hydro hybrid system and Latin hypercube sampling and k-means based scenario analysis is proposed to model total forecast error of power output for the renewable power plants. Also, for forecasting and modeling a daily electricity loads Cho et al. (Cho et al., 2013) offers a hybrid approach. As an illustration of real-life dataset of France between 1996 and 2009 the proposed approach has resulted no longer the right method for the winter season. Short- or medium-term forecast is more reliable and productive for extreme seasonal environmental situations like low wind summers or desperately cold winter, and to measure uncertainties effectively Gaussian stochastic based machine learning process model is proposed by Ahmad et al (Ahmad et al., 2021). The study demonstrates that the proposed model using real-time data is capable of forecasting wind and solar power at three different locations with satisfactory accuracy.

Another study is carried out by Rakpho and Yamaka (Rakpho & Yamaka, 2021) used Bayesian Vector Autoregressive model (BVAR) with using Economic Policy Uncertainty (EPU) index for prediction of energy demand and supply. Results shows that the performance of BVAR model has been strengthen by EPU for forecasting energy demand, but poor forecasting performance for energy supply. In another study, a multi agent based heuristic optimization model is proposed to obtain demand satisfaction and sustainable energy level for distribution planning and control of various located storage devices. According to the proposed model, it minimizes surplus energy and storage better than the centralized model (Mohammed & Al-Bazi, 2021).

Interval optimization model is suggested to form the uncertainty of the upstream net price, and demand response program is used to modify energy usage for economic goals for photovoltaic hybrid system (Taghizadeh et al., 2020). The effect of climate change complimentary between solar and wind hybrid energy system is evaluated within the model intercomparison project phase 6 to achieve the stabilize of supply and demand, and the future complementarity is evaluated using two index, similarity index and concurrency index (Costoya et al., 2023). Maghami and Mutambara (Maghami & Mutambara, 2023) mentioned the challenges of hybrid energy systems. Here, various Artificial intelligent methods are presented for reducing the environmental impact, managing the increasing demand, and minimizing the supply gap. The feasibility of solar HES is analyzed for conservation park (Sreenath et al., 2023). The technical, economic and environmental performance analysis has been carried out.

As the energy usage areas change, hybrid systems are diversified. For the consumers purchasing and selling the energy become more flexible. Improvement of home energy management system (HEMS) needs effective energy consuming, getting high satisfaction. Therefore, for HEMS a multi objective MILP model is proposed to optimize energy cost (Huy et al., 2023). For a residential area hybrid solar energy system are used to generate electricity, and TRNSYS simulation software is proposed for optimal cost and economically friendly solution. Yuan et al. (X. Yuan et al., 2022) proposed the HWEH that is based on dual rotor inversion efficiency enhancement mechanism to collect wind energy for railways. However, the proposed system is not conducted. China’s Yalong River is a case study to formulate daily generation scheduling energy system, and three stage model is suggested. The results shows that while comparing two and three stage model for this case study, three stage model is better to increase the average energy production of wind, solar, hydro complementary system (K. Huang et al., 2023).

Several studies in the literature propose Hybrid Energy Storage Systems (HESS) to achieve the desired performance by integrating different technologies. These studies include various HESS configurations based on storage type, interface, control method, and provided service (Magesh, 2025); facilitating uninterrupted energy management by mitigating the impact of fluctuating energy inputs between distributed energy storage systems and distributed energy resources (Memon et al., 2025); and ensuring a stable frequency in a remote microgrid powered by solar and wind energy through the use of a battery bank without requiring an external electricity supply (Padmashini et al., 2025), a coordinated control strategy for the energy power generation system in a lithium iron phosphate-supercapacitor hybrid energy storage unit (Y. Zhang et al., 2025).

As a case study in Chine’s Jilin Province for a co-scheduling model of wind, photovoltaic, hydro, thermal hybrid energy system MOHPSO is conducted for solving the optimal scheduling problem, however the algorithm has not had reliable and effective solutions (X. Li et al., 2023). To achieve optimum PV sizing and design the systematic revive was conducted (Kazem et al., 2022). CO2 emission is one of the main issues of the electricity generation. Therefore, for the hybrid wind, photovoltaic system neuro fuzzy direct power control is suggested to improve the system performance and generated electricity quality. Energy management algorithm is used to balance of demand, mitigation fluctuation. The results demonstrates that these will increase the equipment life span for the hybrid system (Sahri et al., 2023) for the rural areas a centralized solar and biogas heating system is suggested, and for analyzing energy and performance thermodynamic model is described. The HES limited biomass raw material is adequate for single solar or biogas hybrid system as a solution (Chen et al., 2023).

Table 1. List Of The Related Studies.

Paper	Energy Type	The Aim of Study	Methodology /Review
(Suganthi & Samuel, 2012)	overall energy	to examine the different energy demand forecasting models	Time series model, regression model, econometric model, ARIMA model, integrated models
(Kannan & Vakeesan, 2016)	solar energy	to negotiate driving forces, trends of world’s energy scenario	Review
(Lewis, 2007)	solar energy	to capture, convert and stored cost effectively for providing widespread energy sources	to conversion energy optimizing using Si-based solar cells is better for fixed costs, and the form of chemical bonds is attractive for massive energy storage.
(Kucukali & Baris, 2010)	Thermal Power	to forecast electricity demand of Turkey	Fuzzy logic algorithm

Table 2 (continued). List Of The Related Studies.

Paper	Energy Type	The Aim of Study	Methodology /Review
(Mahesh & Sandhu, 2015)	Hybrid wind/photovoltaic energy	to present a systematic review of HES with PV/wind with battery storage	Review
(Rakpho & Yamaka, 2021)	fossil fuels and renewable energies	to forecast energy supply and demand depending on power of economic policy uncertainty	Bayesian Vector Autoregressive model
(Tavner et al., 2010)	wind energy	to investigate the impact of weather and location on wind turbine failure ratio	the cross-correlation between failures, locations, wind speed, changes of weather
(Jahanpour et al., 2016)	wind energy	to sustain wind energy distribution	Best Matching protocol and DCS Protocol
(Ifaei et al., 2017)	hybrid solar and wind energy	to obtain hourly power demand in different sites	DaSOSaCa algorithm
(IRENA, 2019)	all forms of renewable energy	renewable energy capacity statistics	reporting to use of national statistical offices, government departments, regulators and power companies
(Cho et al., 2013)	coal and gas plants, nuclear plants, wind turbines.	To forecast and model the daily electricity load	Hybrid approach (including weekly and daily average load) by fitting a optimizing355 additive model
(Ahmad et al., 2021)	solar and wind power	short- and medium-term energy power forecasting	Gaussian stochastic-machine learning based model
(Rakpho & Yamaka, 2021)	fossil fuels and renewable energies	forecasting economic policy uncertainty for demand and supply	Bayesian Vector Autoregressive model
(Mohammed & Al-Bazi, 2021)	wind power	planning and management of the allocation of renewable energy sources	Multi Agent-Based Heuristic Optimization model
(Al-Abri & Okedu, 2023)	overall energy	using the econometric model to forecast energy demand	load forecast algorithm
(Syama & Ramprabhakar, 2022)	wind	wind speed forecasting	Bayesian optimized algorithm
(Shivam et al., 2020)	hybrid solar/wind	optimizing the multiple objectives of system in terms of different economic factors	multi objective pareto set analysis
(Z. Zhang et al., 2020)	wind/solar/hydro hybrid system	siding the uncertainties in short term optimal model	the simulation estimation method, the divided weighted long-short term memory network

Table 3 (continued). List Of The Related Studies.

Paper	Energy Type	The Aim of Study	Methodology /Review
(W. Yuan et al., 2021)	hydro hybrid energy	maximizing the energy generation, increasing the penetration of energy	A chance constrained programming based stochastic optimization model
(Zhu et al., 2020)	wind, photovoltaic HES	stochastic optimization of wind, photovoltaic HES	Parallel swarm optimization algorithm
(Sreenath et al., 2023)	Solar hybrid energy system	economical, technical, environmental performance analysis	HOMER Pro software
(Huy et al., 2023)	Integration of solar and electric vehicle	consuming effective energy, high satisfaction level for home energy management system	multi objective MILP
(X. Yuan et al., 2022)	hybrid solar energy system	finding cost optimal and ecofriendly solution	TRNSYS simulation software
(Maghami & Mutambara, 2023)	Hybrid energy system	Challenges of hybrid energy system	Review
(Zhou et al., 2023)	Hybrid wind energy harvester	Generating power for power sensor, and small electrical devices for railway	Dual inversion efficiency enhancement mechanism
(Taghizadeh et al., 2020)	photovoltaic hybrid energy system	optimizing performance of under uncertainties	demand response program, interval optimization technique
(Costoya et al., 2023)	HES wind / solar energy	achieving supply and demand balance through the renewable energies	Multi model ensemble of ten global climate model
(Lu et al., 2021)	Wind/photovoltaic/hydro hybrid system	Optimization model for short term joint operation of hybrid stream	MILP, hypercube sampling and k-means
(K. Huang et al., 2023)	Hybrid wind, solar, hydro complementary system	Modeling the daily electric generation scheduling of hybrid system	Three stage model
(X. Li et al., 2023)	Wind, photovoltaic, hydro, thermal hybrid energy system	Economical, carbon emission analysis of hybrid system	MOHPSO
(Kazem et al., 2022)	Solar photovoltaic energy systems	Optimum social, economic, environmental, technical design	review
(Sahri et al., 2023)	Hybrid system based DFIG, wind, photovoltaic power system	Enhancing system performance and quality with a new intelligent control development of hybrid photovoltaic, wind system	Neuro fuzzy direct power control
(Chen et al., 2023)	Hybrid solar, biogas heating system	Developing the sustainability and economy of the system to satisfy demand	A centralized SBHHS and thermodynamic model is proposed to analyze and measure of the system's energy and performance

Forecasting electricity demand, determination of capacity, meeting the demand, and capacity utilization are hard and complicated to decide due to the stochastic nature and uncertainty in human behavior and it is evident from the studies in the literature. However, it is understandably seen from the literature the decision mechanism is not adequate with those methods.

The decision mechanism in the problem has hard and complicated procedure, and more improved and faster algorithm is required. Moreover, maintaining a balance between demand and capacity remains important, even when forecasting models are used to forecast energy demand. Therefore, the proposed DCSP will be milestone for the literature. Here, the use of DDM in energy industry presents an application field for the literature due insufficient study. The proposed DCSP academically contributes the science. The list of the papers used in the literature is demonstrated in Table 1.

3. Methodology

In this research, each energy power plant in CNE, $\boldsymbol{E} = \{\boldsymbol{e_1^p}, \dots, \boldsymbol{e_n^p}\}$, is a self-operative organization, the self-decision maker. Each $\boldsymbol{e_n^p}$ are not competing even if they are producing similar products. For this purpose, CNE can fulfill the electricity demand of each community in the network and provide a sustainable and efficient energy network for each, $\boldsymbol{e_n^p}$. DCSP provides coordination among networked energy power plants.

In the network the demand and capacity sharing decisions, some fundamental decisions should be considered during the DCSP procedure such as deciding on accepting orders, demand sharing, and capacity sharing (Yoon & Nof, 2010b). Every energy power plant in a CN receives its own order quantity. Based on the power plant capacity constraint, it is assumed that whensoever the customer order is placed, the order is evaluated as providing it provides the required amount of electricity. The order cannot be accepted if the power plant does not have sufficient capacity. The power plant then collaborates effectively with another power plant by sharing demand and capacity. Therefore, the order could be acceptable in this situation, which creates mutual benefits for both parties. Therefore, DCSP is an effective way here to fulfill the order request and get an additional demand from another power plant. After receiving the orders, three scenarios are possible; 1) the power plant meets demand without additional capacity, 2) the power plant meets demand with additional capacity, and 3) the power plant could not meet demand.

When the available capacity is insufficient to fulfill the received order, a demand sharing decision is made for the possible power plant. In contrast, if additional capacity is available after fulfilling the received order, it can be shared with a power plant whose demand cannot be met.

Energy power plants' capacities are greater than the energy demands of each responsible community. However, extraordinary demand fluctuations or planned or unplanned interruptions and malfunctions of electricity generation cause an increase in unsatisfied demand or a decrease in capacity utilization. During a period, e_n^p may not be able to fulfill own demand with its capacity when $d_{it} - c_{jt} > 0$. Then, e_n^p seeks a surplus capacity from another power plant to do minimize the unfulfillment demand rate which is calculated as in Equation 1.

$$ad_{it}^u = d_{it} - c_{jt} \tag{1}$$

Moreover, if $d_{it} - c_{jt} < 0$ exist, then e_n^p seeks another power plant to send excess capacities to increase its capacity utilization rate. In these two cases, e_n^p searches to maximize its local targets by meeting its customer demand at the time t, d_{it}. The amount of excess capacity is calculated as in Equation 2.

$$ec_{jt} = c_{jt} - d_{jt} \tag{2}$$

At any time t, the collaboration between $e_i^p$and e_j^p could appear if ad_{it}^u and ec_{jt} are greater than 0. Obtaining the sustainability of minimizing lost sales, producing cost, and maximizing the total profit and demand fulfillment rate, capacity utilization rate are aimed in the protocol. The protocol's pseudocode is presented in Table 2. The suggested DCSP starts if $e_i^p$and e_j^p are greater than zero simultaneously, and continuous over the collaboration time until ad_{jt}^{ur} or $ad_{it}^d = 0$ $\forall e_i^p$ and e_j^p. The objective of the proposed DCSP is to achieve the most reciprocal advantages by directed the best-matching problem between $e_i^p$and e_j^p. The best matching problems are accepted as an expansion of the stable marriage problems which require *O(k^2)* time. However, a Pareto optimality condition could be satisfied by a decision protocol (Bhargava et al., 2016).

Table 2. DCSP Pseudocode.

DCSP Pseudocode	
Step 1.	Calculate ec_{jt} and ad_{it}^u for each power plant
Step 2.	Analyze $ec_{jt} > 0$ and $ad_{it}^u > 0$
2.a.	If $ec_{jt} > 0$, then send Capacity Sharing Proposal (CSP_{jt})
2.b.	If $ad_{it}^u > 0$, then send Demand Sharing Proposal (DSP_{it})
Step 3.	Analyze CSP_{jt} and DSP_{it} ($\forall\, i \in I, \forall\, j \in J, \forall\, t \in T$)
3.a.	Check if $CSP_{jt} \geq DSP_{it}$, then go to Step 4.
3.b.	Check if $DSP_{it} \geq CSP_{jt}$, then go to Step 4.

Table 2 (continued). DCSP Pseudocode.

Step 4.	Request ec_{jt} from e_i^p and go to Step 6.
Step 5.	Request ad_{it}^u from e_j^p
Step 6.	Update ad_{jt}^{ur}, ad_{it}^d.
Step 7.	Check ad_{jt}^{ur} *or* $ad_{it}^d > 0$, then go to Step 1.
Step 8.	Terminate algorithm.

3.1. Mathematical formulation

A coordination mechanism needs to be designed to optimize the demand and capacity sharing decision among all e_n^p. ad_{it}^u and $ec_{jt} > 0$ which are computed in Equations 1 and 2, refers to the amount of maximum surplus demand and capacity. The aim of DSCP is to distribute ad_{it}^u *and* ec_{jt} among each e_n^p. The objective function of the DSCP is described as the profit maximization of each e_n^p when ad_{it}^u and $ec_{jt} > 0$ which is defined as in Equation 3.

$$Z_{\max} = \begin{cases} d_{jt}S^p + ae_{ijt}^p PD - c_{jt}C^p & if\ c_{jt} > d_{jt} \\ ae_{ijt}^s S^p - ae_{ijt}^p C^r & if\ c_{jt} \leq d_{jt} \end{cases} \tag{3}$$

The notations used in model are presented in Table 3.

Table 4. List of Notations

Indices		
i	=	index of demand of the e_i^p ($i = 1, \ldots, N$)
j	=	index of capacity of the e_j^p($j = 1, \ldots, N$)
t	=	time period ($t = 1, \ldots, T$)
Parameters		
d_{it}	=	demand of e_i^p at time t
c_{jt}	=	capacity of e_j^p at time t
c_{jt}^r	=	realized capacity of e_j^p at time t
w_{jt}	=	working status of e_j^p at time t
Scalars		
C^p	=	production unit cost of electricity
I^p	=	revenue from network processing
C^{up}	=	cost of sending unprocessed electricity
C^r	=	cost of receiving from the distribution network
S^P	=	selling price of electricity
PD	=	profit from selling to distribution network
Positive variables		
ae_{ijt}^p	=	the amount of produced electricty at time t
ae_{ijt}^s	=	the shared amount of electricty at time t
ec_{jt}	=	excess capacity of e_j^p at time t
ad_{it}^u	=	the amount of unsatisfied demand of e_i^p at time t
ae_{jt}^d	=	the amount of capacity obtained from network to e_j^p at time t
ad_{ijt}^{ud}	=	the amount of unsatisfied demand after collaboration at time t
ad_{jt}^{ur}	=	unsatisfied demand remaining after distribution at time t
td_{ij}	=	the total satisfied demand at time t
		Table 5 (continued). List of Notations
ad_{it}^d	=	the amount of unsatisfied demand after collaboration at time t
α	=	collaboration rates
Binary variables		
f_{ijt}	=	$\begin{Bmatrix} 1, & \text{if the power plants runs} \\ 0, & \text{otherwise} \end{Bmatrix}$
a_{ijt}	=	$\begin{Bmatrix} 1, & \text{if collaboration exists} \\ 0, & \text{otherwise} \end{Bmatrix}$

Equation 3 presents the objective function in the following equations:
1) profit of e_n^p, π_n^p from demand satisfaction by its own capacity with or without shared capacity describe as in Equation 4.

$$\pi_n^p = \begin{cases} d_{jt}S^p , & if\ c_{jt} > d_{it} \\ ae_{ijt}^s S^p, & if\ c_{jt} \leq d_{it} \end{cases} \tag{4}$$

2) the profit of e_j^p by sending surplus capacity to e_i^p describe as in Equation 5.

$$\pi_n^s = \begin{cases} ae_{ijt}^s PD , & if\ c_{jt} > d_{it} \\ 0, & if\ c_{jt} \leq d_{it} \end{cases} \tag{5}$$

3) the production cost e_n^p, ρ_n, defined as in Equation 6.

$$\rho_n = \begin{cases} c_{jt}^r C^p , & if\ c_{jt} > d_{it} \\ 0, & if\ c_{jt} \leq d_{it} \end{cases} \tag{6}$$

4) the cost of buying surplus capacity from e_j^p, ρ_j as in Equation 7.

$$\rho_j = \begin{cases} 0, & if\ c_{jt} > d_{it} \\ ae_{ijt}^s C^r, & if\ c_{jt} \leq d_{it} \end{cases}. \tag{7}$$

.

In Equation 3, $\sum_{i=1}^{N} ae_{ijt}^{d} = c_{jt} - d_{it}\ if\ c_{jt} > d_{it}$, and $\sum_{i=1}^{N} ae_{ijt}^{d} = c_{jt} - d_{it}\ if\ c_{jt} \leq d_{it}$ are performed. $Z_{\max}$ can be demonstrated as in Equation 8.

$$Z_{\max} = \begin{cases} d_{it}S^p + (c_{jt} - d_{it})\ PD - c_{jt}C^p & if\ c_{jt} > d_{it} \\ (c_{jt} - d_{it})\ S^p - (c_{jt} - d_{it})\ C^r & if\ c_{jt} \leq d_{it} \end{cases}$$

$$Z_{\max} = \begin{cases} (d_{jt}(S^p - PD) + c_{jt}(PD - C^p) & if c_{jt} > d_{it} \\ (c_{jt}(S^p - C^r) - d_{it}(S^p - C^r)) & if\ c_{jt} \leq d_{it} \end{cases} \tag{8}$$

So, the expected value of $Z_{\max}$ can be demonstrated as in Equation 9.

$$\begin{aligned} E[Z_{\max}] &= \int_{c_{jt}}^{\infty} (\ d_{it}(S^p - PD) + c_{jt}(C^p - PD)\ )\ f(d_{it}) dd_{it} \\ &\quad + \int_{0}^{c_{jt}} (c_{jt}(S^p - C^r) - d_{it}(S^p - C^r))\ \ f\big(d_{jt}\big) dd_{it} \\ &= (S^p - PD) \int_{c_{jt}}^{\infty} d_{it} f\big(d_{jt}\big) dd_{it} + (C^p - PD) \int_{c_{jt}}^{\infty} c_{jt}\ f(d_{it}) dd_{it} \\ &\quad + (S^p - C^r) \int_{0}^{c_{jt}} c_{jt} f\big(d_{jt}\big) dd_{it} - (S^p - C^r) \int_{0}^{c_{jt}} d_{it}\ f(d_{it}) dd_{it} \end{aligned} \tag{9}$$

After, the 1st and 2nd differentiation of Equation 9 can be shown as

$$\frac{dE[Z_{\max}]}{dc_{jt}} = (PD - C^p) \int_{c_{jt}}^{\infty} c_{jt}\ f(d_{it}) dd_{it} + (S^p - C^r) \int_{0}^{c_{jt}} c_{jt} f(d_{it}) dd_{it}$$

$$\frac{dE[Z_{\max}]}{dc_{jt}} = (PD - C^p)(1 - F(c_{jt})) + (S^p - C^r) F\big(c_{jt}\big)$$

$$\frac{d^2 E[Z_{\max}]}{dc_{jt}^2} = (S^p - C^r - PD + C^p) f\big(c_{jt}\big)$$

So, it is demonstrated that $Z_{\max}$ is a convex function since $\frac{d^2 E[Z_{\max}]}{dc_{jt}^2} = (S^p - C^r - PD + C^p) f\big(c_{jt}\big) > 0$ and $S^p, C^r, PD, and\ C^p$ are non-negative with the condition of $S^p > PD,\ C^p > C^r$ and $f\big(c_{jt}\big) > 0$. The result indicates that achieving the most expected profit

$\forall e_n^p$ regarding collaboration between ad_{it}^u and ec_{jt} gives the optimal solutions in a polynomial time. The objective function maximizes the total profit of the power in the network during the decision horizon. Under the consideration of demand and supply uncertainty of electricity production is developed for modeling with DCSP by the following Equations from 10 to 26:

$$\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{t=1}^{T} f_{ijt} = 1 \qquad \forall(i=j),t \qquad (10)$$

$$ec_{jt} + \sum_{i=1}^{N} ae_{ijt}^{p} < c_{jt}^{r} \qquad \forall(i \neq j),t \qquad (11)$$

$$c_{jt}^{r} - \left[\sum_{i=1}^{N} f_{ijt}\, d_{it}\right] = ec_{jt}\,\alpha \qquad \forall j,t \qquad (12)$$

$$ae_{ijt}^{p} < f_{ijt}\ x\ R \qquad \forall i,j,t \qquad (13)$$

$$ae_{ijt}^{s} = d_{it} \qquad \forall(i=j),t \qquad (14)$$

$$ae_{ijt}^{s} = R\ x\ f_{ijt} \qquad \forall(i \neq j),t \qquad (15)$$

$$\sum_{i=1}^{N} ae_{ijt}^{s} > ec_{jt} \qquad \forall(i \neq j),t \qquad (16)$$

$$\sum_{j=1}^{N} ae_{ijt}^{s} = ad_{it}^{u} \qquad \forall(i=j),t \qquad (17)$$

$$\sum_{j=1}^{N} ad_{ijt}^{ud} < ad_{it}^{u} \qquad \forall i,t \qquad (18)$$

$$ad_{ijt}^{ud} < R\ x\ a_{ijt} \qquad \forall(i \neq j),t \qquad (19)$$

$$\sum_{j=1}^{N} a_{ijt} < 3 \qquad \forall i,t \qquad (20)$$

$$\sum_{i=1}^{N} ad_{ijt}^{ud} = ae_{jt}^{d} \qquad \forall j,t \qquad (21)$$

$$ad_{jt}^{ur} = ec_{jt} - \sum_{i=1}^{N} dt_{ijt} \qquad \forall j,t \qquad (22)$$

$$\sum_{t=1}^{T} (ae_{ijt}^{p} + ad_{ijt}^{ud}) = td_{ij} \qquad \forall i,j \qquad (23)$$

$$\sum_{j=1}^{N} ae_{ijt}^{s} - \sum_{j=1}^{N} ad_{ijt}^{ud} > ad_{it}^{d} \qquad \forall i,t \qquad (24)$$

$$ae_{ijt}^{p}, ae_{ijt}^{s}, ec_{jt}, ad_{it}^{u}, ae_{jt,,}^{d}, ad_{ijt}^{ud}, ad_{jt}^{ur}, td_{ij}, ad_{it}^{d} \geq 0 \qquad \forall i,j,t \qquad (25)$$

$$f_{ijt}, a_{ijt} \in \{0,1\} \qquad \forall i,j,t \qquad (26)$$

Equation 10 ensures that power plant activity generates electricity at time *t*. Equation 11 implies that each time the amount of produced electricity is equal to the real capacity of the power plant. Equation 12 demonstrates the excess capacity of the power plant before collaboration at time *t*. Equation 13 makes sure that the electricity generation power plant meets its own needs first. The power plant cannot cooperate without meeting its demand. Equation 14 ensures that an unsatisfied demand amount is sent to CN when there is not enough capacity at time *t*. Equation 15 enables the decision to assign the unmet demand at time *t*. Equation 16 power plant that accepts unmet demand amount receives up to its surplus capacity at time *t*. Equation 17 calculates the unmet demand quantity at time *t*. Equation 18 calculates the total quantity of surplus demand sent to another plant at time *t*. Equation 19 provides that an assignment of surplus demand quantity to a potential power plant at time *t*. Equation 20 makes sure that the number of max collaborations on the network at each period. Equation 21 provides the total demand attained from another plant at time *t*. Equation 22 calculates the unsatisfied demand attained from a other plant at time t. Equation 23 calculates the total met demand quantity at time *t*. Equation 24 calculates the quantity of unmet demand at time *t* after collaboration. Equations 25 and 26 show in order of non-negative variables and binary variables.

4. Experimental Results and Analysis

This part provides parameter settings and numerical examples of power plant collaboration to demonstrate and assess the performance of the model.

4.1. Parameter setting

In the study, 16 independent power plants are simulated as a CNE in four independent communities. Four power plants are in each community, and these power plants are primarily responsible for the community where they are located. In each community, HES is designed in different combinations including wind energy, hydroelectric power, solar energy, and thermal power plant thermal power plant as shown in Figure 3. Also, each community provides the supply-demand balance within itself.

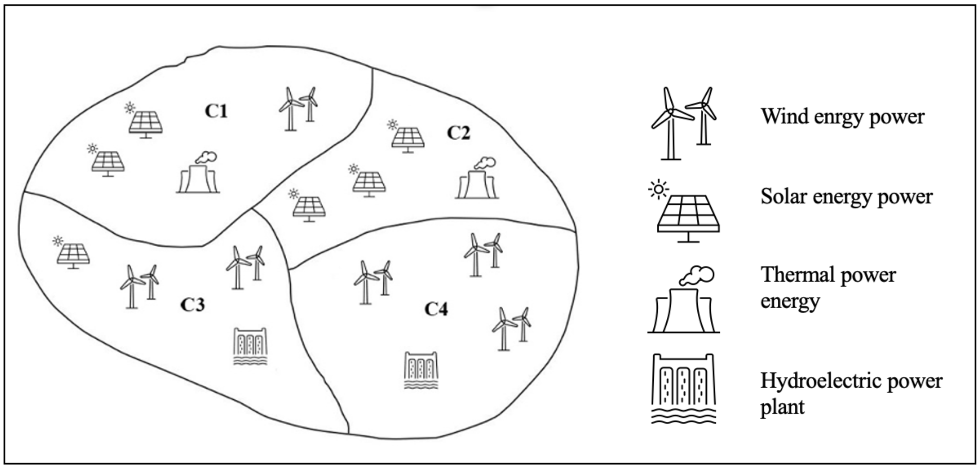

Figure 3. Communities in the Proposed Case Scenario.

Various power plants are collaborating to display and examine the performance of the suggested protocol. Three power plant collaboration scenarios are designed as no collaboration scenario, partial collaboration scenario, and complete collaboration scenario with changing α values. In no collaboration model (α=0), each power plant tries to handle its electricity demand with its available capacity; however, without demand and capacity partake with other power plants exist. A partial collaboration model (α= (0,1)) is defined to illustrate demand and capacity sharing among collaborative power plants. In a complete collaboration model (α=1), total excess demand and excess capacity among collaborative power plants are shared when necessary. If there is an excess capacity or rejected order, demand and capacity are shared with power plants in a HES.
The general features and assumptions of the protocol are the demand and capacity of each power plant is supposed to be greater than zero, provided there are no disruption or failures. Each power plant operates under a finite capacity when sharing considerations are applied. The demand distribution for a group of collaborative plants at a given time t is formed as a normal distribution. Additionally, the available capacity of each plant is influenced by its working condition, which is represented by a Normally distributed p-value. If p>P, the power plant is considered to be non-operational.

4.2. Simulation results and analyses

To display the performance of the proposed DCSP, the total profit and demand accomplishment ratio under the various α parameters is performed for each region (C_1, C_2, C_3, C_4). The details of the simulation parameter setting are abbreviated in Table 4.

Table 6. Summary of parameter setting.

Number of communities	$C = \{1,2,3,4\}$
Number of power plants	$E = \{1, \ldots, 16\}$
α values	$\alpha = \{ 0.1y \mid y \in [0,10], y \in Z \}$
p values	$p = \{ 0.05y \mid y \in [10,18], y \in Z \}$
Demand distribution of a customer orders	*N= {2500, 10}*
Capacity distribution of a customer order	*N= {3000, 10}*
Simulation time (*sn*) and replication	10000 and 1000
Unit cost of electricity production [₺/unit]	C^p= 60 ₺/unit
Unit profit from network processing [₺/unit]	I^p= 60 ₺/unit
Unit cost of receiving from the network [₺/unit]	C^r= 65 ₺/unit
Unit selling price of electricity to customer[₺/unit]	SP= 75 ₺/unit
Unit profit from selling to network [₺/unit]	PD= 70 ₺/unit

Figures 3, 4 and 5 illustrate the total profit of every community with changing α values. It is observed that the profit of every region increases as the α value increases. Figures 3 and 4 indicates that with each increase in the α value the total profit of C_1 is rising. According to this Figures 3 and 4, it displays that when the alpha value is increased from 0 to 1, the total profit is increased from 430,1 to 1126,1. In terms, the total profit of C_1 is increased by 161,8% which is shown in Figure 5. Also, similar results appear in C_2, C_3, and

C_4 as follow 166,4%,192,2%,151%, respectively. The changing in the total profit of every community shows similar trends as demonstrated in Figures 3, 4 and 5.

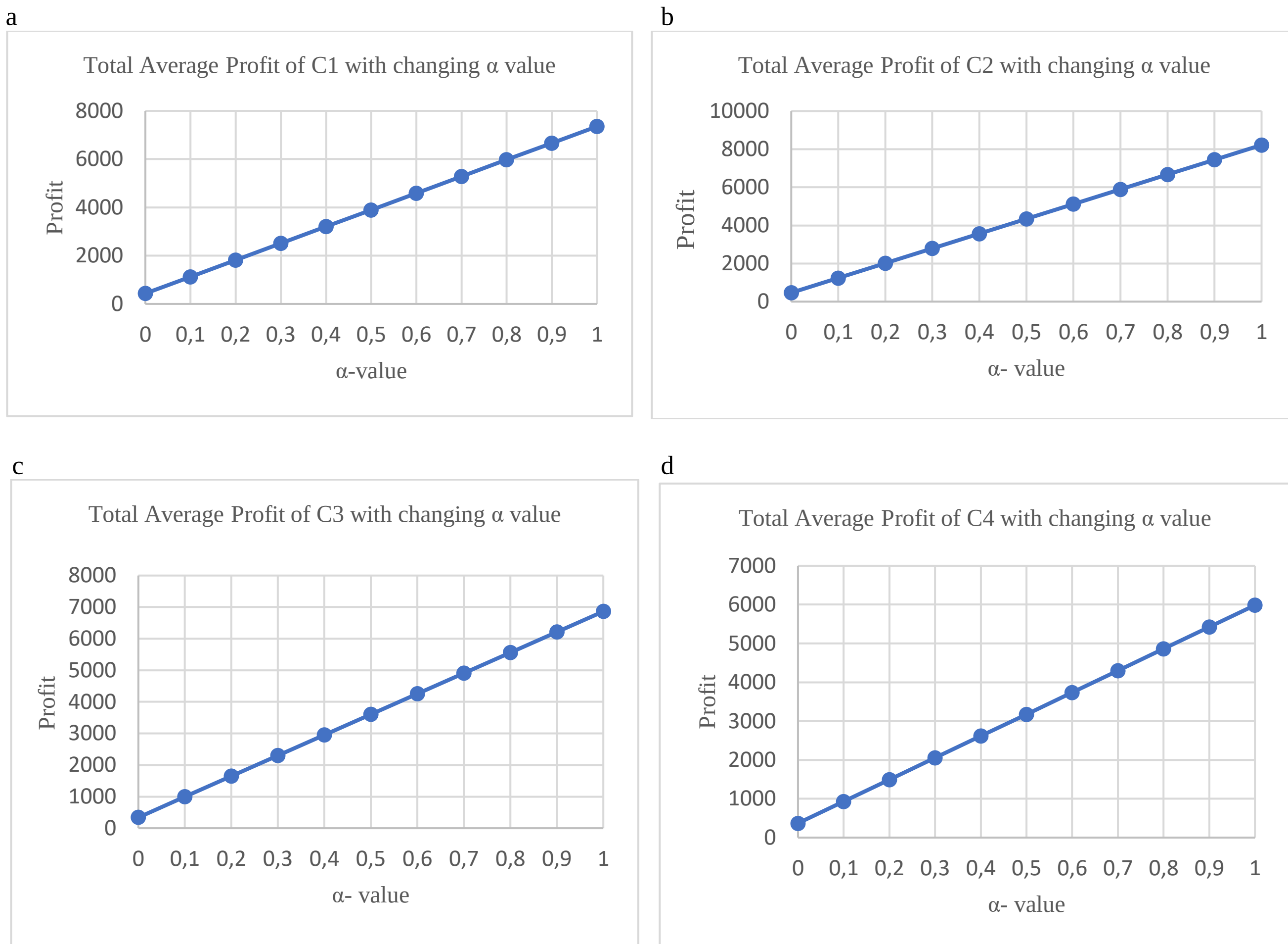

Figure 1. (a) Total Average Profit of C1;**(b)** Total Average Profit of C2;**(c)** Total Average Profit of C3;**(d)** Total Average Profit of C4

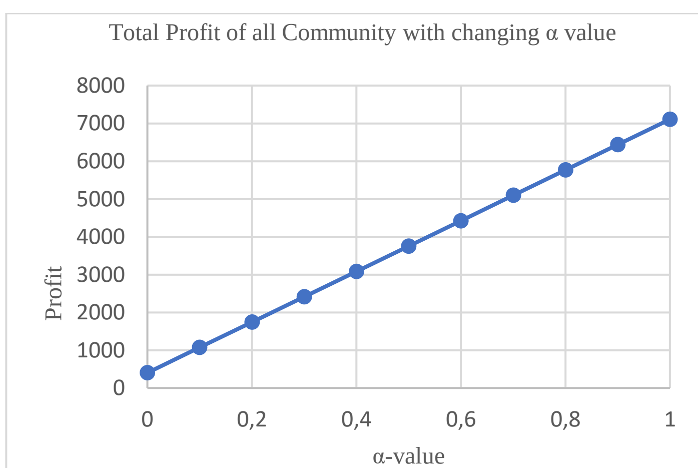

Figure 4. Total Average Profit of All Community.

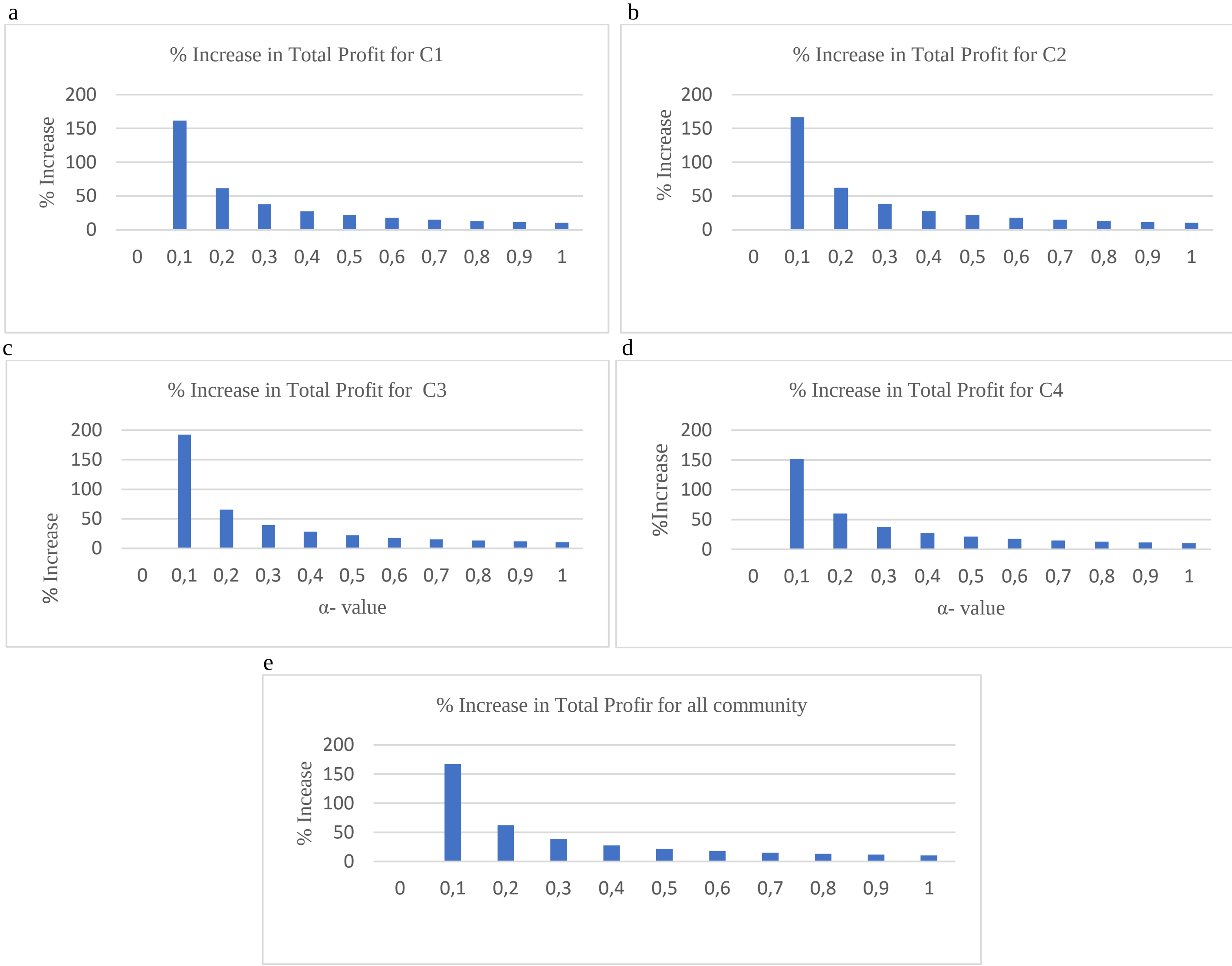

Figure 5. **(a)** Total Average Profit Changings in Percentage of C1; **(b)** Total Average Profit Changings in Percentage of C2; **(c)** Total Average Profit Changings in Percentage of C3; **(d)** Total Average Profit Changings in Percentage of C4; **(e)** Total Average Profit Changings in Percentage of All Community.

The model aims to maximize the total profit and includes four different functions: 1) profit from selling to CN, π_n^s, dark blue box, 2) production cost of e_n^p, ρ_n , orange box, 3) the cost of buying surplus capacity from e_j^p, ρ_j , grey box, and 4) profit of e_n^p, π_n^p, light blue box. For every community, the objective function has been calculated and demonstrated in Figure 6 and 7 with various α-values. While total profit is increasing, and the costs are decreasing when α→1.

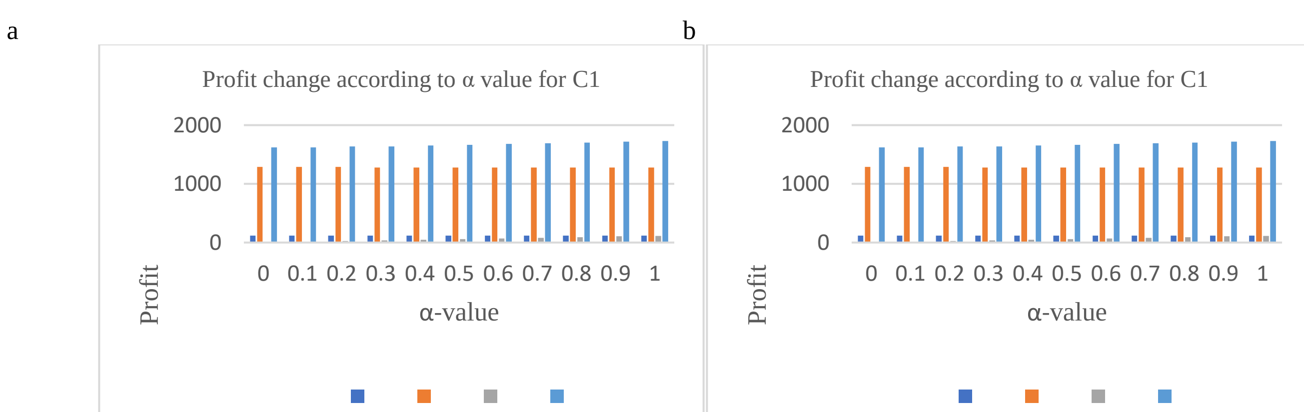

Figure 6. **(a)** Profit Change for C1; **(b)** Profit Change for C2.

Figure 7. (a) Profit Change for C3; **(b)** Profit Change for C4.

In the proposed model, DCSP deals with two situations which are 1) failure of power plant because of the probabilistic nature of the power plants, and 2) inadequate demand due to the inadequate capacity. Thus, the total profit of every power plant shows changes in various amounts. For example, the total profit is calculated by taking different failure values between 50% and 90% of the power plant under the different α-values demonstrate in Figure 6. It is sighed that each component of the objective function rises for each community when α→1. For each community, changing the failure of power plant and α-values effect the total profit, and even if the failure of power plant increase, with increasing collaboration between the power plant an increase in total profit is observed which is demonstrated in Figure 8.

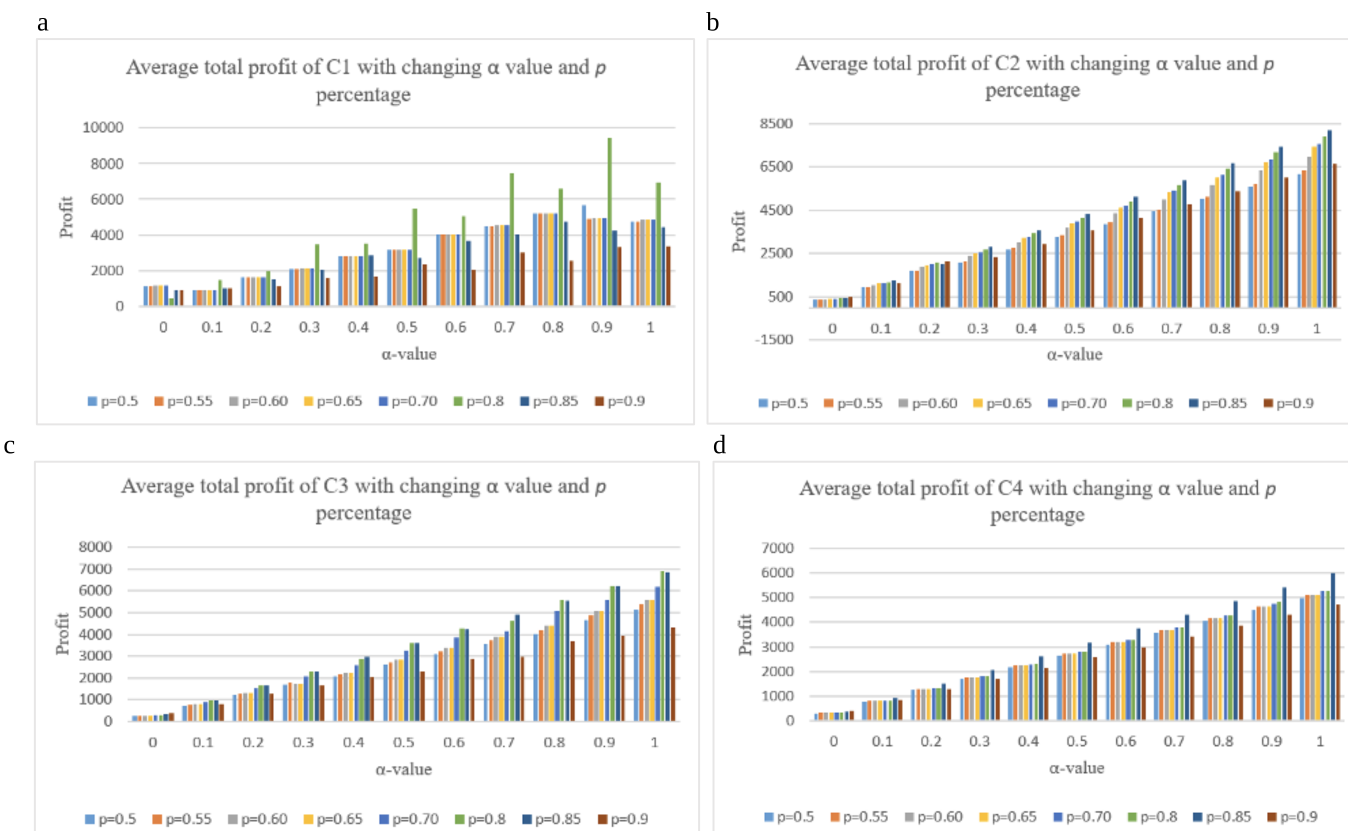

Figure 8. **(a)** Average Total Profit of C1 Under Various α and *p* Values; **(b)** Average Total Profit of C2 Under Various α and *p* Values; (**c**) Average Total Profit of C3 Under Various α and *p* Values; **(d)** Average Total Profit of C4 Under Various α and *p* Values.

Regardless of the scenario, each facility generates the optimal amount of electricity to meet its demand if the power plant is functioning. With no collaboration scenario, excess capacity occurs because the capacity of each power plant exceeds the demand of its responsibility region; therefore, the CN model is applied to share the excess capacity in cases where a power plant cannot fulfill the demands.

According to the experimental results, collaboration has a positive impact on overall profit. It is important to test how the model changes by using different collaboration scenarios. Therefore, eleven different α values between [0,1] are applied to evaluate the effectiveness of the proposed DSCP. Also, the results are tested by the analysis of variance to test if the variation between the means of the eleven groups is significant or not. The results suggest that there is a notable difference within the groups as displayed in Table 5. One-Way ANOVA computes a *p*-value that is less than 0,05 to test the difference between groups, and for each community, *p*-values are shown in Table 5. All the p-values of communities are below 0.05 i.e., for the *p*-value of C_1 is $3{,}67\text{x}10^{-32}$, the *p*-value of C_2 is $7{,}97\ \text{x}10^{-32}$, the *p*-value of C_3 is $2{,}15\ \text{x}10^{-32}$ and, the *p*-value of C_4 is $4{,}19\ \text{x}10^{-32}$ that are less than 0,05, which shows that within the groups there is a statistically important variation with regard to increase in the total profit.

Table 7. One-Way ANOVA for C1, C2, C3, C4.

ANOVA	C1					
Variance source	*SS*	*df*	*MS*	*F*	*P-value*	*F criterian*
Between groups	791398140,4	10	79139814,04	31,12047839	3,67E-32	1,892653475
Within groups	391624165	154	2543014,058			
Total	1183022305	164				
ANOVA	**C2**					
Variance source	*SS*	*df*	*MS*	*F*	*P-value*	*F criterian*
Between groups	991866916,3	10	99186691,63	102,5432279	7,97345E-63	1,892653475
Within groups	148959134,8	154	967267,1093			
Total	1140826051	164				
ANOVA	**C3**					
Variance source	*SS*	*df*	*MS*	*F*	*P-value*	*F criterian*
Between groups	702056139,5	10	70205613,95	26,03016471	2,15135E-28	1,892653475
Within groups	415351369	154	2697086,812			
Total	1117407508	164				
ANOVA	**C4**					
Variance source	*SS*	*df*	*MS*	*F*	*P-value*	*F criterian*
Between groups	520030434	10	52003043,4	100,0085727	4,19259E-62	1,892653475
Within groups	80077822	154	519985,8571			
Total	600108256	164				

CN imitates the operation of four unrelated power plants in four distinct communities. In each community, different energy sources create a HES. Each power plant in a HES has its capacity and demand at time *t*. With the effect of the α parameter, at some time *t*, some of the energy sources could not generate electricity. In this situation, demand and capacity sharing within the community occur simultaneously in a HES. To demonstrate the performance of the recommended DCSP the performance measure is utilized for the total demand achievement rate of HES when α→1 is illustrated in Figure 7. Demand achievement rate of a power plant is calculated as in Equation 27.

$$\varphi_t = \frac{ae_{ijt}^p + ae_{jt}^d}{\sum_i^N d_{it}} \tag{27}$$

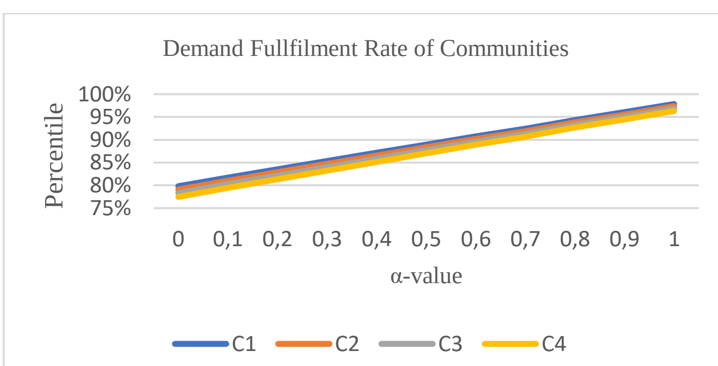

Figure 9. Demand Fulfillment Rate of Communities.

Figure 9 indicates that when α = 0, the demand achievement rate of the C_1, C_2, C_3, and C_4 are 79,23%, 78,40%, 77,51%, and 76,55%, respectively. As the α-value improves the demand achievement rate of each community is increasing. α → 1, the demand achievement rate of each community has reached the highest value; C_1, C_2, C_3, and C_4 are 97,78%, 97,26%, 96,71%, and 96,12%. Therefore, the changes in the demand achievement rate between no collaboration and complete collaboration for each C_1, C_2, C_3, and C_4 are increased up to 23,42%, 24,06%, 24,77%, and 25,56% respectively.

5. Conclusion and Future Directions

DSCP is proposed for defining the conditions for beneficiary collaboration among power plants in a HES in this study. To overcome the changes in supply-demand balance, CNE methodology based on CNP is applied to DSCP. This research examines the impressiveness of the recommended method to distributing and assigning demand and capacity through the networked power plants in a HES. In literature, there are various application examples of CNP; however, this research is the first research that applied CNP methodology to coordinate the decisions within HES power plants. A key attribute of the recommended protocol is that it facilitates collaboration between the power plants resulting in an increase in the demand fulfillment rate, mutual benefits, maximizing profit, and an increase in surplus capacity for all plants within system.

Failure of power plants and unsatisfied demand at any time are the two main scenarios of the recommended model. A sample scenario featuring four communities and sixteen plants is provided to showcase the impact of the proposed model. A performance analysis of the suggested protocol is also conducted under different types of collaboration and failure rates. The total profit and demand achievement rate of each community are calculated in such circumstances. For C_1 the total profit is increased from 430,1 to 7357,6 when α → 1. Similar situations are valid for C_2 (from 465,7 to 8218,3, C_3 (from 339,26 to 6862,2), and C_4 (from 369,9 to 5983,9). Moreover, ANOVA one-way test was conducted to confirm the performance of the suggested DCSP, the demand achievement ratio for every community improvement as the collaboration ratio rises. According to numerical examples and analyses, the DCSP can increase the total profit and the demand achievement ratio within the community.

The enhancement of renewable energy industry is a proof of the improvement of macroeconomic. Also, advancement in science and technology relies on the use of energy. It is more efficient to meet the required energy needs with a hybrid energy system consisting of more than one energy source instead of single energy power. The hybrid energy system in which region having different climate and certain geographic conditions has some risks and necessities. This work demonstrates how important the efficiency of the energy sources themselves in HES.

The DCS protocol is very important for energy management as the suggested system model can respond to dynamic conditions and uncertainties. Here, the energy management system was designed to manage supply-demand balance in network system. Some of the advantages is like; first, the increase of demand fulfillment rate due to the collaborative network, second, the increase in the capacity utilization rate by using the excess capacity in other energy sources in cases where the facility is not operating, or the production capacity is insufficient due to environmental conditions. Distributed decision-making protocol is selected for the hybrid energy system's energy management and its performance was examined and evaluated during different energy power working status, different collaboration rates in this work.

This work has been directed to achieve mutual benefit for each energy producers in hybrid energy system for the first time. A new DCS protocol is proposed to improve the reliability and sustainability of Hybrid Energy Systems (HESs). This protocol optimizes energy distribution, balances supply and demand, and allows adaptive resource allocation. This innovative approach enhances system resilience and efficiency. Moreover, CN lifespan and sustainability will be investigated in upcoming research directions. It is also strongly proposed that as a new case study the collaborative network in various field should be considered with new parameters and constraints to achieve the precise decisions. Additionally, different types of HES could be considered when determining what type of power plant is most appropriate for the management of HES in a sustainable manner. DCSP could be designed by incorporating fuzzy logic to interpret its effectiveness under uncertain environments.

References

Ahmad, T., Zhang, D., & Huang, C. (2021). Methodological framework for short-and medium-term energy, solar and wind power forecasting with stochastic-based machine learning approach to monetary and energy policy applications. *Energy*, *231*, 120911. https://doi.org/10.1016/j.energy.2021.120911

Ajidarma, P., Nof, S. Y., Pradana, R. A., Nugroho, W. A., & Halim, A. H. (2022). Preemptive Demand and Capacity Sharing Learning Protocols Using Long Short-Term Memory (LSTM) Neural Network Autoencoders. *IFAC-PapersOnLine*, *55*(10), 1798–1803. https://doi.org/10.1016/j.ifacol.2022.09.659

Al-Abri, A., & Okedu, K. E. (2023). Overview of the Global Electricity System in Oman Considering Energy Demand Model Forecast. *Energy Engineering: Journal of the Association of Energy Engineering*, *120*(2), 409–423. https://doi.org/10.32604/ee.2023.020375

Al-khaykan, A., Al-kharsan, I. H., Ali, M. O., Alrubaie, A. J., Fakhruldeen, H. F., & Counsell, J. M. (2023). *Impact of Multi-Year Analysis on the Optimal Sizing and Control Strategy of Hybrid Energy Systems*. 1–17.

Bhargava, R., Levalle, R. R., & Nof, S. Y. (2016). A best-matching protocol for order fulfillment in re-configurable supply networks. *Computers in Industry, 82*, 160–169. https://doi.org/10.1016/j.compind.2016.07.001

Chen, Y., Guo, M., Liu, Y., Wang, D., Zhuang, Z., & Quan, M. (2023). Energy, exergy, and economic analysis of a centralized solar and biogas hybrid heating system for rural areas. *Energy Conversion and Management*, *276*(13), 116591. https://doi.org/10.1016/j.enconman.2022.116591

Cho, H., Goude, Y., Brossat, X., & Yao, Q. (2013). Modeling and forecasting daily electricity load curves: A hybrid approach. *Journal of the American Statistical Association*, *108*(501), 7–21. https://doi.org/10.1080/01621459.2012.722900

Costoya, X., deCastro, M., Carvalho, D., & Gómez-Gesteira, M. (2023). Assessing the complementarity of future hybrid wind and solar photovoltaic energy resources for North America. *Renewable and Sustainable Energy Reviews*, *173*(November 2022). https://doi.org/10.1016/j.rser.2022.113101

Ghofrani, M., & Hosseini, N. N. (2016). Optimizing Hybrid Renewable Energy Systems: A Review. *Sustainable Energy - Technological Issues, Applications and Case Studies*. https://doi.org/10.5772/65971

Global Futures Report - REN21. (n.d.). Retrieved May 23, 2022, from https://web.archive.org/web/20190724164150/https://www.ren21.net/reports/global-futures-report/

Huang, C. Y., & Wu, Y. W. (2003). Decision model for partnership development in virtual enterprises. *International Journal of Production Research, 41*(9), 1855–1872. https://doi.org/10.1080/0020754031000087210

Huang, K., Liu, P., Kim, J. S., Xu, W., Gong, Y., Cheng, Q., & Zhou, Y. (2023). A model coupling current non-adjustable, coming adjustable and remaining stages for daily generation scheduling of a wind-solar-hydro complementary system. *Energy*, *263*(PB), 125737. https://doi.org/10.1016/j.energy.2022.125737

Huy, T. H. B., Dinh, H. T., & Kim, D. (2023). Multi-objective framework for a home energy management system with the integration of solar energy and an electric vehicle using an augmented ε-constraint method and lexicographic optimization. *Sustainable Cities and Society*, *88*(November 2022), 104289. https://doi.org/10.1016/j.scs.2022.104289

Ifaei, P., Karbassi, A., Jacome, G., & Yoo, C. K. (2017). A systematic approach of bottom-up assessment methodology for an optimal design of hybrid solar/wind energy resources – Case study at middle east region. *Energy Conversion and Management*, *145*(2017), 138–157. https://doi.org/10.1016/j.enconman.2017.04.097

IRENA. (2019). Renewable capacity statistics 2019, International Renewable Energy Agency (IRENA), Abu Dhabi. In *International Renewable Energy Agency (IRENA), Abu Dhabi*.

Jahanpour, E., Ko, H. S., & Nof, S. Y. (2016). Collaboration protocols for sustainable wind energy distribution networks. *International Journal of Production Economics*, *182*(July 2015), 496–507. https://doi.org/10.1016/j.ijpe.2016.09.010

Kannan, N., & Vakeesan, D. (2016). Solar energy for future world: - A review. *Renewable and Sustainable Energy Reviews*, *62*, 1092–1105. https://doi.org/10.1016/j.rser.2016.05.022

Kazem, H. A., Chaichan, M. T., Al-Waeli, A. H. A., & Gholami, A. (2022). A systematic review of solar photovoltaic energy systems design modelling, algorithms, and software. *Energy Sources, Part A: Recovery, Utilization and Environmental Effects*, *44*(3), 6709–6736. https://doi.org/10.1080/15567036.2022.2100517

Kucukali, S., & Baris, K. (2010). Turkey's short-term gross annual electricity demand forecast by fuzzy logic approach. *Energy Policy*, *38*(5), 2438–2445. https://doi.org/10.1016/j.enpol.2009.12.037

Kumar, C. M. S., Singh, S., Gupta, M. K., Nimdeo, Y. M., Raushan, R., Deorankar, A. V., Kumar, T. M. A., Rout, P. K., Chanotiya, C. S., Pakhale, V. D., & Nannaware, A. D. (2023). Solar energy: A promising renewable source for meeting energy demand in Indian agriculture applications. *Sustainable Energy Technologies and Assessments*, *55*(November 2022), 102905. https://doi.org/10.1016/j.seta.2022.102905

Lewis, N. S. (2007). Toward cost-effective solar energy use. *Science*, *315*(5813), 798–801. https://doi.org/10.1126/science.1137014

Li, J. (2023). Evaluation of dynamic growth trend of renewable energy based on mathematical model. *Energy Reports*, *9*, 48–56. https://doi.org/10.1016/j.egyr.2022.11.139

Li, X., Yang, W., Zhao, Z., Wang, R., & Yin, X. (2023). Advantage of priority regulation of pumped storage for carbon-emission-oriented co-scheduling of hybrid energy system. *Journal of Energy Storage*, *58*(December 2022), 106400. https://doi.org/10.1016/j.est.2022.106400

Lu, L., Yuan, W., Su, C., Wang, P., Cheng, C., Yan, D., & Wu, Z. (2021). Optimization model for the short-term joint operation of a grid-connected wind-photovoltaic-hydro hybrid energy system with cascade hydropower plants. *Energy Conversion and Management*, *236*. https://doi.org/10.1016/j.enconman.2021.114055

Magesh, S. (2025). Distributed energy storage systems: Hybrid energy storage systems. *Distributed Energy Storage Systems for Digital Power Systems*, 109–147. https://doi.org/10.1016/B978-0-443-22013-5.00011-3

Maghami, M. R., & Mutambara, A. G. O. (2023). Challenges associated with Hybrid Energy Systems: An artificial intelligence solution. *Energy Reports*, *9*, 924–940. https://doi.org/10.1016/j.egyr.2022.11.195

Mahesh, A., & Sandhu, K. S. (2015). Hybrid wind/photovoltaic energy system developments: Critical review and findings. *Renewable and Sustainable Energy Reviews*, *52*, 1135–1147. https://doi.org/10.1016/j.rser.2015.08.008

Memon, M. M., Halepoto, I. A., Abro, M. A. J., & Khuhawar, F. Y. (2025). Distributed energy storage systems for distributed energy resources integration. *Distributed Energy Storage Systems for Digital Power Systems*, 319–358. https://doi.org/10.1016/B978-0-443-22013-5.00015-0

Mertens, S. (2022). Design of wind and solar energy supply, to match energy demand. *Cleaner Engineering and Technology*, *6*, 100402. https://doi.org/10.1016/j.clet.2022.100402

Minowa, M., Ito, K., Sumi, S. I., & Horii, K. (2012). A Study of Lightning Protection for Wind Turbine Blade by Using Creeping Discharge Characteristics Masayuki. *2012 International Conference on Lightning Protection (ICLP), Vienna, Austria*, 12–15.

Mohammed, N., & Al-Bazi, A. (2021). A multi agent-based optimisation model for the distribution planning and control of energy-based intermittent renewable sources. *International Journal of Energy Research*, *45*(13), 19316–19330. https://doi.org/10.1002/er.7044

Padmashini, R. K., Lakshmi, D., Rajeshkumar, J. N., Sivaraman, P., Rajasree, R., & Chenniappan, S. (2025). Energy management for distributed energy storage system. *Distributed Energy Storage Systems for Digital Power Systems*, 183–199. https://doi.org/10.1016/B978-0-443-22013-5.00003-4

Rakpho, P., & Yamaka, W. (2021). The forecasting power of economic policy uncertainty for energy demand and supply. *Energy Reports*, *7*, 338–343. https://doi.org/10.1016/j.egyr.2021.06.059

Reddy, S. S. (2017). Optimization of Renewable Energy Resources in Hybrid Energy Systems. *Journal of Green Engineering*, *7*(1), 43–60. https://doi.org/10.13052/JGE1904-4720.7123

Sahri, Y., Tamalouzt, S., Belaid, S. L., Bajaj, M., Ghoneim, S. S. M., Zawbaa, H. M., & Kamel, S. (2023). Performance improvement of Hybrid System based DFIG-Wind/PV/Batteries connected to DC and AC grid by applying Intelligent Control. *Energy Reports*, *9*, 2027–2043. https://doi.org/10.1016/j.egyr.2023.01.021

Shivam, K., Tzou, J. C., & Wu, S. C. (2020). Multi-objective sizing optimization of a grid-connected solar-wind hybrid system using climate classification: A case study of four locations in Southern Taiwan. *Energies*, *13*(10). https://doi.org/10.3390/en13102505

Smith, R. G. (1980). The Contract Net Protocol: High-Level Communication and Control in a Distributed Problem Solver. *IEEE Transactions on Computers*, *C–29*(12), 1104–1113. https://doi.org/10.1109/TC.1980.1675516

Sreenath, S., Azmi, A. M., & Ismail, Z. A. M. (2023). Feasibility of solar hybrid energy system at a conservation park: Technical, economic, environmental analysis. *Energy Reports*, *9*, 711–719. https://doi.org/10.1016/j.egyr.2022.11.065

Suganthi, L., & Samuel, A. A. (2012). Energy models for demand forecasting - A review. *Renewable and Sustainable Energy Reviews*, *16*(2), 1223–1240. https://doi.org/10.1016/j.rser.2011.08.014

Syama, S., & Ramprabhakar, J. (2022). Multistep Ahead Solar Irradiance and Wind Speed Forecasting using Bayesian Optimized Long Short Term Memory. *7th International Conference on Communication and Electronics Systems, ICCES 2022 - Proceedings*, *Icces*, 164–171. https://doi.org/10.1109/ICCES54183.2022.9835840

Taghizadeh, M., Bahramara, S., Adabi, F., & Nojavan, S. (2020). Optimal operation of storage-based hybrid energy system considering market price uncertainty and peak demand management. *Journal of Energy Storage*, *30*(April), 101519. https://doi.org/10.1016/j.est.2020.101519

Tavner, P. J., Greenwood, D. M., Whittle, M. W. G., Gindele, R., Faulstich, S., & Hahn, B. (2010). Study of weather and location effects on wind turbine failure rates. *Wind Energy*, *16*(2), 175–187. https://doi.org/10.1002/we.538

Wei, H., Hongxuan, Z., Yu, D., Yiting, W., Ling, D., & Ming, X. (2019). Short-term optimal operation of hydro-wind-solar hybrid system with improved generative adversarial networks. *Applied Energy*, *250*(April), 389–403. https://doi.org/10.1016/j.apenergy.2019.04.090

Wei, Y., Liu, H., Gu, K., & Li, D. (2007). Contract net based scheduling approach using interactive bidding for dynamic job shop scheduling. *IEEE ICIT 2007 - 2007 IEEE International Conference on Integration Technology*, 281–286. https://doi.org/10.1109/ICITECHNOLOGY.2007.4290478

Wu, J., Levi, N., Araujo, R., & Wang, Y. G. (2023). An evaluation of the impact of COVID-19 lockdowns on electricity demand. *Electric Power Systems Research*, *216*(November 2022), 109015. https://doi.org/10.1016/j.epsr.2022.109015

Yilmaz, I., & Yoon, S. W. (2020). Dynamic-distributed decisions and sharing protocol for fair resource sharing in collaborative network. *International Journal of Production Economics*, *226*(January). https://doi.org/10.1016/j.ijpe.2020.107644

Yoon, S. W., & Nof, S. Y. (2010a). Demand and capacity sharing decisions and protocols in a collaborative network of enterprises. *Decision Support Systems*, *49*(4), 442–450. https://doi.org/10.1016/j.dss.2010.05.005

Yoon, S. W., & Nof, S. Y. (2010b). Demand and capacity sharing decisions and protocols in a collaborative network of enterprises. *Decision Support Systems*, *49*(4), 442–450. https://doi.org/10.1016/j.dss.2010.05.005

Yuan, W., Wang, X., Su, C., Cheng, C., Liu, Z., & Wu, Z. (2021). Stochastic optimization model for the short-term joint operation of photovoltaic power and hydropower plants based on chance-constrained programming. *Energy*, *222*, 119996. https://doi.org/10.1016/j.energy.2021.119996

Yuan, X., Heikari, L., Hirvonen, J., Liang, Y., Virtanen, M., Kosonen, R., & Pan, Y. (2022). System modelling and optimization of a low temperature local hybrid energy system based on solar energy for a residential district. *Energy Conversion and Management*, *267*(March), 115918. https://doi.org/10.1016/j.enconman.2022.115918

Zhang, H., Liao, K., Yang, J., Yin, Z., & He, Z. (2025). Long-term and Short-term Coordinated Scheduling for Wind-PV-Hydro-Storage Hybrid Energy System based on Deep Reinforcement Learning. *IEEE Transactions on Sustainable Energy*. https://doi.org/10.1109/TSTE.2025.3529215

Zhang, Y., Han, Z., Tian, B., Chen, N., & Fan, Y. (2025). Coordinated Control Strategy of New Energy Power Generation System with Hybrid Energy Storage Unit. *Energy Engineering: Journal of the Association of Energy Engineering*, *122*(1), 167. https://doi.org/10.32604/EE.2024.056190

Zhang, Z., Qin, H., Li, J., Liu, Y., Yao, L., Wang, Y., Wang, C., Pei, S., & Zhou, J. (2020). Short-term optimal operation of wind-solar-hydro hybrid system considering uncertainties. *Energy Conversion and Management*, *205*(October 2019), 112405. https://doi.org/10.1016/j.enconman.2019.112405

Zhou, X., Dai, C., Liu, G., Tan, X., Zhang, Z., Pan, Y., Pan, H., & Ahmed, A. (2023). A hybrid wind energy harvester based on a double-rotor reverse synergy mechanism for high-speed railway. *Sustainable Cities and Society*, *90*(August 2022), 104389. https://doi.org/10.1016/j.scs.2022.104389

Zhu, F., Zhong, P. an, Xu, B., Liu, W., Wang, W., Sun, Y., Chen, J., & Li, J. (2020). Short-term stochastic optimization of a hydro-wind-photovoltaic hybrid system under multiple uncertainties. *Energy Conversion and Management*, *214*(1), 112902. https://doi.org/10.1016/j.enconman.2020.112902