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CHAPTER 1

The Effects of Microplastics On the Endocrine System

Cağla Kurkcu[1] & Sebnem Gun[2]

INTRODUCTION

Water is essential for all living species and serves as a crucial resource for numerous human activities, including home use, agriculture, and industry. In recent years, alarming contaminants identified in wastewater, surface water, and groundwater have adversely affected water quality, with concentrations ranging from few ng L^{-1} to µg L^{-1} in essential water sources, including surface water, groundwater, and drinking water (Verlicchi et al., 2010). Micropollutants can infiltrate urban sewage systems via multiple channels. These systems can be contaminated by anthropogenic discharges via urine and feces, inadequate waste management, or the leaching of pesticides and biocides from urban regions during precipitation (Margot et al., 2013).

These micropollutants include surfactants, pharmaceuticals, personal care products, pesticides, endocrine disruptors, illegal drugs, gasoline additives, and many other compound groups (Luo et al., 2014). One of the key characteristics of these compounds is that they can cause adverse effects without needing to persist in the environment for long periods. This is because their continuous entry into the environment compensates for high transformation or removal rates (Verlicchi et al., 2010).

Micropollutants consist of many different compounds, including pesticides, pharmaceuticals, cosmetics, flame retardants, perfumes, waterproofing treatments, plasticizers, and insulation foams. Among these substances, pharmaceuticals and personal care products (PCPs) and endocrine disrupting chemicals (EDCs) stand out as anthropogenic pollutants frequently encountered in water sources (Kim & Zoh, 2016). Controlling the entry of micropollutants into aquatic environments is quite difficult, as these compounds are widely used to improve quality of life, and demand for them is increasing every year.

Research indicates that medicines and EDCs are found at substantial concentrations in several aquatic settings, including surface water, groundwater, drinking water, and wastewater (Snyder et al., 2003). Nonetheless, conventional treatment methods employed in wastewater treatment facilities are not intended

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to fully eradicate micropollutants. Consequently, residues of these chemicals are often detected in treated wastewater. Consequently, these micropollutants endure in diverse aquatic settings, including surface waters, endangering ecosystems and human health (Rogowska et al., 2020).

Micropollutants in aquatic environments induce numerous detrimental effects, including both acute and chronic toxicity in microorganisms, endocrine diseases linked to endocrine disruptors, and the emergence of antibiotic resistance (Huerta-Fontela et al., 2011). While certain countries and areas have implemented laws for certain micropollutants, there are no uniform norms or criteria governing the discharge of these substances from Wastewater Treatment Plants (WWTPs). Additional investigation of the environmental persistence of micropollutants and their impacts on human and ecological health is essential for determining regulatory thresholds for these substances (Petrie et al., 2015).

Mitigating the prevalence of micropollutants in aquatic systems and eradicating them using conventional and innovative treatment methodologies is a paramount concern for environmental and human health. This study will examine the impact of micropollutants on the endocrine system.

1. Endocrine Disruptors

The endocrine system is a control and communication system composed of hormone-producing glands that regulate the body's fundamental functions, such as growth, metabolism, reproduction, and stress response (Bergman et al., 2013). Endocrine disruptors are organic or synthetic substances that interact with the endocrine system, affecting hormonal production and balance in organisms, resulting in adverse effects in healthy individuals and their progeny. A significant category of micropollutants comprises naturally occurring hormones, including estrogens and androgens from human secretions, alongside anthropogenic endocrine-disrupting compounds like 17α-ethinylestradiol present in contraceptive tablets (Johnson & Sumpter, 2001). Table 1 lists endocrine-disrupting micropollutants and their uses (Dogruel et al., 2022). Moreover, it has been discovered that several substances not explicitly engineered as endocrine disruptors, including phthalates, also alter hormonal systems. Substances include phosphorus flame retardants, biocides, industrial pollutants, anti-inflammatory medications, nonsteroidal anti-inflammatory pharmaceuticals, and antiarrhythmic treatments have been identified as influencing human estrogen and androgen receptors (Itzel et al., 2018).

Table 1. Endocrine-Disrupting Micropollutants (Dogruel et al., 2022).

Micropollutants	Uses
17β-estradiol (E2)	Natural estrogen
17α-ethinyl estradiol (EE2)	Synthetic estrogen
Bisphenol-A	Plasticizer
Paraben	Preservative chemical
PFOA (Perfluorooctanoic acid)	Protective coating material
Atrazine	Pesticide
Carbamazepine	Antiepileptic drug
Diclofenac	Anti-inflammatory drug
Sulfamethoxazole	Antibiotic

Over the past two decades, the presence of endocrine-disrupting chemicals (EDCs) in aquatic ecosystems has been a key area of environmental research. These chemicals have been shown to reduce fertility and cause intersex disorders and sexual abnormalities in humans and wildlife. However, increasing amounts of data indicate that endocrine disruption may arise not only from EDCs, but also from other categories of molecules (Ammann et al., 2014). EDCs and pharmaceutical-chemical personal care products (PPCPs) typically exhibit greater polarity than conventional pollutants, with most possessing acidic or basic functional groups. These chemical characteristics, coupled with their low concentrations (i.e. <1 μg/L), present distinct challenges in treatment processes and analytical detection (Snyder et al., 2003; Cesaro & Belgiorno, 2016).

1.1. 17 – β – estradiol, E2

Estradiol (E2), also referred to as estrogen, is a steroid hormone that serves as the principal female sex hormone. It is crucial in controlling female reproductive cycles, namely influencing estrus and menstrual periods. It also governs the development of secondary sexual traits, including breast enlargement, hip expansion, and female adipose distribution. The growth and maintenance of reproductive organs, including mammary glands, uterus, and vagina, during adolescence, maturity, and pregnancy is crucial. Estradiol significantly influences several tissues, including bone, adipose tissue, dermis, liver, and cerebral structures (Mechoulam et al., 1984; Saldanha et al., 2011). Estradiol levels in men are much lower than in women, but this hormone still has important functions in men. Estradiol is found not only in humans and other mammals, but also in many vertebrates, crustaceans, insects, fish, and other animals (Wang et al., 2015). Estradiol is primarily produced in the follicles of the ovaries and in tissues such as the testes, adrenal glands, fat, liver, breasts, and brain. Estradiol, produced in the body from cholesterol, is formed through intermediate products such as androstenedione and testosterone (Simpson & Davis, 2001; Santen & Simpson, 2019). In women, the ovaries stop producing estrogen during menopause, and estradiol levels drop significantly. Estradiol is used not only as a natural hormone but also for medical purposes such as menopause treatment and hormone therapy for transgender women (Hembree et al., 2017).

Estradiol, as a micropollutant in the environment, can have significant effects on the endocrine system when released into aquatic environments. E2, which enters water from wastewater treatment plants, domestic waste, or agricultural pesticides, can cause hormonal imbalances in aquatic organisms even at low concentrations (Rochman et al., 2014; Caldwell et al., 2012). In fish, effects such as the emergence of intersex characteristics (a mixture of female and male sex characteristics), decreased reproductive capacity, and sexual development disorders can be observed (Rochman et al., 2014; Kidd et al., 2007). The release of this hormone into the environment can threaten biological diversity in aquatic ecosystems and disrupt ecosystem balance (Snyder et al., 2003).

The micropollutant properties of E2 can also indirectly threaten human health. E2, which can be found even at low levels in drinking water sources, can disrupt hormone balance when ingested, creating adverse effects on reproductive health (Caldwell et al., 2010; Caldwell et al., 2012). This can increase hormone-related diseases such as breast cancer risk in women (Rudel et al., 2011). Furthermore, the long-term effects of estradiol on living organisms in the environment can jeopardize the sustainability of ecosystems. Therefore, the environmental monitoring of estradiol and other endocrine-disrupting chemicals and the control of their effects are of great importance (Bergman et al., 2013).

1.2. 17α-ethinyl estradiol (EE2)

Ethinylestradiol is a synthetic estrogen hormone frequently utilized in contraceptive pills alongside progestins. Frequent adverse consequences of EE2 encompass breast pain, headaches, fluid retention, and nausea. In males, the usage of estrogenic agents may correlate with breast development, feminization, hypogonadism, and sexual dysfunction (Hembree et al., 2017). Graver however less frequent adverse effects encompass blood clots, including venous thromboembolism, hepatic impairment, and an elevated chance of specific hormone-sensitive malignancies (Haverinen et al., 2022). Consequently, the utilization of formulations containing EE2 must be meticulously assessed, considering the individual's medical history, risk factors, and contraindications.

Endocrine-disrupting substances, including ethinylestradiol, in aquatic systems can lead to significant health issues for both aquatic creatures and humans (Caldwell et al., 2012; Bergman et al., 2013). Possible consequences for humans including reproductive health issues, hormone-associated malignancies, and various endocrine system abnormalities. EE2, specifically, can disturb hormonal equilibrium, resulting in issues such as diminished sperm count, infertility, and erectile dysfunction in males. In females, it has been associated with breast cancer, ovarian cancer, and precocious puberty (Rudel et al., 2011). Moreover, individuals exposed to EE2 may develop metabolic diseases, including thyroid dysfunction, obesity, and cardiovascular disease (Bergman et al., 2013).

In aquatic organisms, the effects of EE2 may be more pronounced. In fish, male individuals may exhibit female characteristics (intersex) and reproductive impairments may occur. This can reduce the reproductive success of species in aquatic ecosystems, disrupting ecosystem balance. In other aquatic organisms, such as frogs, reproductive disorders, sexual development abnormalities, and loss of fertility may be observed. These types of effects demonstrate how chemicals in the aquatic environment can affect ecosystems and their potential implications for human health (Rochman et al., 2014).

Figure 1 shows the sources, exposure, and remediation actions of ethinyl estradiol (Aris et al., 2014).

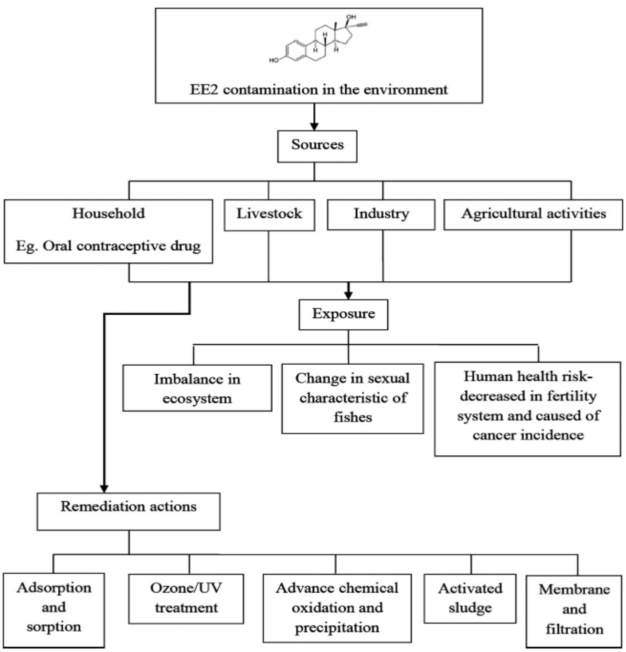

Figure 1. Conceptual diagram of ethinyl estradiol (Aris et al., 2014).

1.3. Bisphenol-A

Bisphenol A (BPA) is an organic compound consisting of two phenol rings linked by a methyl bridge and is commonly used in the production of epoxy resins and polycarbonate plastics. Epoxy resins are widely used in automobile parts, adhesives, PVC pipes, food packaging, and the coating of tin cans (EFSA, 2015). Polycarbonate plastics are preferred in products such as food packaging, automotive lenses, and plastic bottles due to their properties such as transparency, high impact resistance, and resistance to acids and oils. BPA is also used in resin-based dental fillings and bonding agents (Fleisch et al., 2010). BPA's lipophilic characteristics result in its affinity for binding to the solid phase in aquatic conditions, indicated by a log Kow value of 3.32. With the rise in BPA manufacturing, human exposure via environmental and food sources also escalates (Staples et al., 1998).

BPA is recognized as an endocrine-disrupting compound estrogenic activity; however, its estrogen receptor binding potency is approximately 300 – fold lower than 17β - estradiol (Bergeron et al., 1999). At minimal dosages, BPA may result in diminished sperm production, reproductive issues, and sexual dysfunction in males. Moreover, in females, it may lead to complications like polycystic ovary syndrome, recurrent miscarriages, and irreversible alterations in mammary gland development. Fetal development may exhibit health issues such as hypospadias, cryptorchidism (undescended testicles), endometrial hyperplasia, and aberrant karyotypes in persons exposed to BPA (Chitra et al., 2003; Muñoz-de-Toro et al., 2005). Schönfelder et al. (2002) observed that, under typical environmental exposure, BPA concentrations in male fetuses exceeded those in female fetuses. This evidence further underscores the possible detrimental consequences of BPA on human health.

1.4. Paraben

Paraben is a preservative compound frequently utilized in pharmaceutical and cosmetic formulations. This ingredient, notably efficacious against germs and fungi, is present in shampoo, hair conditioner, moisturizing cream, toner, deodorant, perfume, shaving gel, tanning cream, cosmetics, sunscreen, and toothpaste. For many years, parabens have been favored due to their affordability and the ineffectiveness of alternative natural preservatives. Nevertheless, certain studies indicate the presence of parabens in the tumors of breast cancer patients; however, a conclusive association between parabens and cancer development remains unproven. Moreover, parabens may influence the hormonal system due to their estrogen-mimicking capabilities (Harvey et al., 2004; Golden et al., 2005).

Parabens are preservation agents frequently utilized in cosmetics, medicines, and cleaning items (Guo & Kannan, 2013). These chemicals are favored for prolonging product shelf life owing to their efficacy in eliminating germs and fungi. Parabens has endocrine-disrupting qualities and can replicate the activity of the estrogen hormone in the body. Consequently, parabens may adversely impact reproductive health by inducing hormonal abnormalities. Studies indicate that methylparaben and ethylparaben can bind to estrogen receptors and influence hormone levels, thereby adversely affecting reproductive health (Nowak et al., 2021).

The micropolluting characteristics of parabens arise from their capacity to pollute the environment and aquatic ecosystems (Karthikraj & Kannan, 2017; Nowak et al., 2021). Parabens can pollute water systems and persist in water sources for extended durations, typically at low quantities, due to wastewater and environmental contamination. This is a risk to ecosystems and human health. The buildup of parabens in aquatic ecosystems can induce endocrine-disrupting effects on marine organisms (Bereketoglu & Pradhan, 2019). They can adversely impact reproductive health, especially in fish, resulting in diminished sperm production and interrupted reproductive cycles (Bereketoglu & Pradhan, 2019; Nowak et al., 2021). Moreover, parabens that enter the human body via water can lead to health complications, including hormonal disruptions, reproductive disorders, and heightened cancer risk due to prolonged exposure. Consequently, the micropollutant characteristics of parabens and their impact on the endocrine system are critically significant due to their enduring adverse impacts on water contamination and health.

1.5. PFOA (Perfluorooctanoic acid)

Perfluorooctanoic acid (PFOA) is one of the synthetic organofluorine compounds known as per- and polyfluoroalkyl substances (PFASs). This compound is commonly used in industrial production processes as a surfactant and raw material. PFOA, which does not occur naturally in the environment, is used primarily to impart heat resistance to nonstick cookware and to provide stain-resistant properties to surfaces such as fabrics and carpets. The adverse health effects of PFOA were revealed in a study conducted as a result of a class action lawsuit against DuPont. The study found a link between high levels of PFOA exposure, primarily from industrial accidents, and diseases such as kidney cancer, ulcerative colitis, hypercholesterolemia, and hypertension. Listed as an “emerging concern” pollutant by the United States Environmental Protection Agency (EPA) in 2014, many American companies, primarily 3M, the manufacturer of PFOS, have decided to discontinue the production of PFOA (Nicole, 2013).

PFOA interacts with environmental systems, including water and air, accumulates in ecosystems, and infiltrates biological organisms (Sunderland et al., 2019). Humans may be exposed to PFOA, especially via water sources and food. Its micropollutant characteristics arise from its capacity to last in aquatic and terrestrial environments. This chemical can adversely impact aquatic organisms, particularly fish, and disrupt their reproductive cycles due to water pollution (Jantzen et al., 2017).

PFOA is distinguished by its endocrine-disrupting characteristics. This compound possesses a structure capable of inducing hormone-like actions in the body and may have estrogenic capabilities. Research in humans indicates that PFOA negatively impacts reproductive health. PFOA has been identified as a disruptor of hormonal balance by its interaction with estrogen receptors, which can adversely impact reproductive health (Sunderland et al., 2019). Moreover, PFOA has been implicated in health issues including cardiovascular disease, renal carcinoma, hypercholesterolemia, and ulcerative colitis (Barry et al., 2013). The micropollutant characteristics of PFOA and its impact on the endocrine system present a considerable threat to ecosystems and human health.

1.6. Atrazine

Atrazine is a herbicide commonly used to control weeds and is typically used in agricultural fields (U.S. EPA, 2025). This chemical substance is odorless, white powder and is soluble in water. Atrazine is not volatile, reactive, or flammable and is produced in a laboratory setting; it does not occur naturally in the environment (Hayes et al., 2011). In agriculture, it is used primarily on crops such as corn, sugarcane, pineapple, sorghum, and macadamia nuts (Jablonowski et al., 2011). It is also widely used in evergreen tree plantations and forest regrowth processes. Atrazine is also applied to prevent weeds along highway and railroad rights-of-way (U.S. EPA, 2025). This herbicide is effective when sprayed on cultivated areas before crops emerge or after they have grown above ground. It is a compound that can be found as a micropollutant in environmental water sources. Once mixed with water, it has the ability to remain in surface waters and groundwater for long periods of time (Jablonowski et al., 2011). This causes atrazine to accumulate in aquatic ecosystems and lead to environmental pollution. Even at low concentrations, prolonged exposure can negatively impact aquatic life (Hayes et al., 2011).

Atrazine, which has endocrine-disrupting properties, can cause hormonal imbalances in the body. This substance, which has particularly estrogenic effects, can disrupt the functioning of the hormonal system by binding to hormone receptors. Atrazine can cause the development of female characteristics in male aquatic organisms and also cause serious disruptions in reproductive cycles. Atrazine found in water sources can also be transmitted to humans through exposure, and long-term consumption can trigger health problems such as hormonal disorders, reproductive problems, and certain types of cancer. Therefore, atrazine's micropollutant properties and endocrine-disrupting effects pose a major threat to both aquatic life and human health (ATSDR, 2003).

1.7. Carbamazepine

Carbamazepine is a drug commonly used to control seizures, treat bipolar disorder, and manage neuropathic pain (Grunze et al., 2021). However, when released into the environment, it tends to accumulate in water systems as a micropollutant. After passing through water treatment plants, this drug can be found in aquatic environments and may negatively affect biodiversity. Carbamazepine can affect hormonal balance by exhibiting endocrine-disrupting properties (da Silva Santos et al., 2018). Studies show that carbamazepine is particularly effective on the sexual development and reproductive functions of aquatic organisms (da Silva Santos et al., 2018; Ács et al., 2022). These effects can lead to negative consequences in organisms, such as reproductive disorders, changes in sexual dimorphism, and abnormalities in sexual behavior.

Research on people indicates that carbamazepine may induce long-term hormonal disturbances due to its impact on the endocrine system. Carbamazepine may interact with estrogen and androgen receptors, resulting in detrimental consequences on reproductive health. Prolonged exposure may result in issues like monthly irregularities, polycystic ovarian syndrome (PCOS), and infertility, particularly in women. Men may experience health issues including diminished sperm production, reduced testosterone levels, and infertility. Additionally, carbamazepine may adversely affect skin, liver, and renal functioning. The environmental micropollutant effects of carbamazepine present a considerable risk to both the ecosystem and human health (Nevitt et al., 2016; Nevitt et al., 2017).

1.8. Diclofenac

Diclofenac is a nonsteroidal anti-inflammatory drug (NSAID) commonly used to treat pain and inflammation. It is effective in treating many conditions such as rheumatism, arthritis, and headaches (Gan, 2010). However, diclofenac is a micropollutant compound that can cause environmental pollution. It can accumulate in aquatic ecosystems over long periods, creating adverse effects on biological systems (Aus der Beek et al., 2016; Madikizela & Chimuka, 2017). Diclofenac entering wastewater sources can cause harmful effects in aquatic organisms even at low concentrations (Praskova et al., 2014). This substance can disrupt the balance of ecosystems by affecting the reproductive capacity and survival rates of aquatic species.

Considering its effects on the endocrine system, diclofenac exhibits hormone-like effects and can cause disruptions in the reproductive processes of aquatic organisms (Aus der Beek et al., 2016). Studies in fish have shown that diclofenac exposure results in developmental abnormalities in reproductive organs, low reproductive rates, and problems with sexual maturation (Praskova et al., 2014). Similar adverse effects may occur in human health; long-term exposure can lead to hormonal imbalances and reproductive health problems (Aus der Beek et al., 2016). For example, diclofenac can cause decreased testosterone levels in men and menstrual irregularities and polycystic ovary syndrome in women (Kristensen et al., 2018). Furthermore, persistent exposure is believed to elevate the risk of cancer, notably contributing to the onset of diseases such as reproductive organ malignancies (uterine, ovarian) and breast cancer. Consequently, the micropollutant characteristics and endocrine-disrupting effects of diclofenac may provide significant hazards to environmental and human health (Swan et al., 2006).

1.9. Sulfamethoxazole

Sulfamethoxazole is a drug commonly used in antibacterial treatments and has gained importance as a micropollutant due to its release into the environment (Zhang et al., 2023). When released into the environment, it does not biodegrade easily and can persist in water sources for a long time (Patrolecco et al., 2018). This can have significant effects on aquatic ecosystems. Sulfamethoxazole can disrupt the endocrine system by affecting hormones in aquatic environments. Such effects lead to changes in hormone levels, particularly in aquatic organisms. This can lead to reproductive problems in fish, decreased sperm production, and sexual development disorders (Iftikhar et al., 2022).

The impact of sulfamethoxazole on human health also presents possible hazards. Prolonged exposure to this chemical may induce hormonal abnormalities. Such abnormalities may result in conditions like polycystic ovarian syndrome in females and diminished sperm count and quality in males. Moreover, research suggests that sulfamethoxazole may elevate cancer risk and compromise thyroid function. Prolonged exposure may also inhibit the immune system, heightening vulnerability to infections. The micropollutant characteristics of sulfamethoxazole and its impact on the endocrine system may present significant health hazards (Roth et al., 2018; NCBI, 2025).

CONCLUSION

Microplastics (MPs) are a substantial element of environmental contamination and can present severe health hazards when they enter the human body via water sources. Their endocrine-disrupting qualities can disrupt hormonal functions, resulting in a rise in diseases including reproductive system disorders, infertility, pregnancy loss, hypospadias, and prostate and breast cancer. They may also impair thyroid function, leading to obesity and several metabolic problems. The introduction of these compounds into aquatic habitats adversely impacts biodiversity, jeopardizing ecosystem health.

Robust methods are essential to mitigate the environmental and health repercussions of MPs. The use of sophisticated treatment technology, regulation of industrial chemical usage, and oversight of agricultural pesticides can markedly diminish the emission of harmful pollutants into the environment. Moreover, comprehensive scientific research and policies derived from this study should be established to enhance the understanding of impacts on human health.

Public awareness is essential in this process. The significance of water quality must be underscored through educational initiatives and awareness campaigns, while also elevating consciousness regarding the hazards of MP exposure. Governments and health organizations must establish more efficient monitoring and regulatory frameworks to enhance the protection of aquatic ecosystems and biodiversity. A holistic worldwide strategy for micropollutants is essential for environmental and human health preservation.

REFERENCES

Ács, A., Liang, X., Bock, I., Griffitts, J., Ivánovics, B., Vásárhelyi, E., Ferincz, Á., Pirger, Z., Urbányi, B., & Csenki, Z. (2022). Chronic effects of carbamazepine, progesterone and their mixtures at environmentally relevant concentrations on biochemical markers of zebrafish (Danio rerio). Antioxidants, 11(9), 1776. https://doi.org/10.3390/antiox11091776

Agency for Toxic Substances and Disease Registry. (2003). Toxicological profile for atrazine. U.S. Department of Health and Human Services, Public Health Service.

Ammann, A. A., Macikova, P., Groh, K. J., Schirmer, K., & Suter, M. J. F. (2014). LC-MS/MS determination of potential endocrine disruptors of cortico signalling in rivers and wastewaters. Analytical and Bioanalytical Chemistry, 406(29), 7653–7665. https://doi.org/10.1007/s00216-014-8206-9

Aris, A. Z., Shamsuddin, A. S., & Praveena, S. M. (2014). Occurrence of 17α-ethynylestradiol (EE2) in the environment and effect on exposed biota: A review. Environment International, 69, 104–119. https://doi.org/10.1016/j.envint.2014.04.011

Aus der Beek, T., Weber, F.-A., Bergmann, A., Hickmann, S., Ebert, I., Hein, A., & Küster, A. (2016). Pharmaceuticals in the environment—Global occurrences and perspectives. Environmental Toxicology and Chemistry, 35(4), 823–835. https://doi.org/10.1002/etc.3339

Barry, V., Winquist, A., & Steenland, K. (2013). Perfluorooctanoic acid (PFOA) exposures and kidney cancer: A cohort study. Environmental Health Perspectives, 121(11–12), 1313–1318. doi: 10.1289/ehp.1306615

Bereketoglu, C., & Pradhan, A. (2019). Comparative transcriptional analysis of methylparaben and propylparaben in zebrafish. Science of the Total Environment, 671, 129–139. https://doi.org/10.1016/j.scitotenv.2019.03.358

Bergeron, R. M., Thompson, T. B., Leonard, L. S., Pluta, L., & Gaido, K. W. (1999). Estrogenicity of bisphenol A in a human endometrial carcinoma cell line. Molecular and Cellular Endocrinology, 150(1–2), 179–187. https://doi.org/10.1016/S0303-7207(98)00202-0

Bergman, Å., Heindel, J. J., Jobling, S., Kidd, K. A., & Zoeller, R. T., (2013). State of the science of endocrine disrupting chemicals – 2012. Geneva, Switzerland: World Health Organization & United Nations Environment Programme. ISBN 978-92-4-150503-1

Caldwell, D. J., Mastrocco, F., Anderson, P. D., Länge, R., & Sumpter, J. P. (2012). Predicted-no-effect concentrations for the steroid estrogens estrone, 17β-estradiol, estriol, and 17α-ethinylestradiol. Environmental Toxicology and Chemistry, 31(6), 1396–1406. DOI: 10.1002/etc.1825

Caldwell, D. J., Mastrocco, F., Nowak, E., Johnston, J., Yekel, H., Pfeiffer, D., Hoyt, M., DuPlessie, B. M., Anderson, P. D. (2010). An assessment of potential exposure and risk from estrogens in drinking water. Environmental Health Perspectives, 118(3), 338–344. https://doi.org/10.1289/ehp.0900654

Cesaro, A., Belgiorno, V. (2016). Removal of endocrine disruptors from urban wastewater by advanced oxidation processes (AOPs): A review. The Open Biotechnology Journal, 10, 151–172. https://doi.org/10.2174/1874070701610010151

Chen, Y., Vymazal, J., Březinová, T., Koželuh, M., Huang, J., Chen, Z., Kule, L., & Liu, H. (2016). Occurrence, removal and environmental risk assessment of pharmaceuticals and personal care products in rural wastewater treatment wetlands. Science of the Total Environment, 566–567, 1660–1669. https://doi.org/10.1016/j.scitotenv.2016.06.069

Chitra, K. C., Latchoumycandane, C., & Mathur, P. P. (2003). Induction of oxidative stress by bisphenol A in the epididymal sperm of rats. Toxicology, 185(1–2), 119–127. https://doi.org/10.1016/S0300-483X(02)00597-8

da Silva Santos, N., Oliveira, R., Lisboa, C. A., Pinto, J. M. E., Sousa-Moura, D., Camargo, N. S., Perillo, V., Oliveira, M., & Grisolia, C. K. (2018). Chronic effects of carbamazepine on zebrafish: Behavioral, reproductive and biochemical endpoints. Ecotoxicology and Environmental Safety, 164, 297–304. https://doi.org/10.1016/j.ecoenv.2018.08.015

Dogruel, S., Gurel, M. ve PehlivanogluMantas, E. (2022), Mikrokirleticiler: Tanım, Mevzuat ve Ülkemizde Atıksularda ve Yerüstü Sularında Mevcudiyetleri, Çevre, İklim ve Sürdürülebilirlik, 23(2), 133–144.

EFSA Panel on Food Contact Materials, Enzymes, Flavourings and Processing Aids (CEF). (2015). Scientific opinion on the risks to public health related to the presence of bisphenol A (BPA) in foodstuffs. EFSA Journal, 13(1), 3978, 23. https://doi.org/10.2903/j.efsa.2015.3978

Fleisch, A. F., Sheffield, P. E., Chinn, C., Edelstein, B. L., & Landrigan, P. J. (2010). Bisphenol A and related compounds in dental materials. Pediatrics, 126(4), 760–768. https://doi.org/10.1542/peds.2009-2693

Gan, T. J. (2010). Diclofenac: An update on its mechanism of action and safety profile. Current Medical Research and Opinion, 26(7), 1715–1731. https://doi.org/10.1185/03007995.2010.486301

Golden, R., Gandy, J., & Vollmer, G. (2005). A review of the endocrine activity of parabens and implications for potential risks to human health. Critical

Reviews in Toxicology, 35(5), 435–458. https://doi.org/10.1080/10408440490920104

Grunze, A., Amann, B. L., & Grunze, H. (2021). Efficacy of carbamazepine and its derivatives in the treatment of bipolar disorder. Medicina, 57(5), 433. https://doi.org/10.3390/medicina57050433

Guo, Y., & Kannan, K. (2013). A survey of phthalates and parabens in personal care products from the United States and its implications for human exposure. Environmental Science & Technology, 47(24), 14442–14449. https://doi.org/10.1021/es4042034

Harvey, P. W., Everett, D. J., & McAnally, H. M. (2004). Significance of the detection of esters of p-hydroxybenzoic acid (parabens) in human breast tumours. Journal of Applied Toxicology, 24(1), 1–4. https://doi.org/10.1002/jat.957

Haverinen, A. H., Luiro, K. M., Szanto, T., Kangasniemi, M. H., Hiltunen, L., Sainio, S., Piltonen, T. T., Lassila, R., Tapanainen, J. S., & Heikinheimo, O. (2022). Combined oral contraceptives containing estradiol valerate vs ethinylestradiol on coagulation: A randomized clinical trial. Acta Obstetricia et Gynecologica Scandinavica, 101(10), 1102–1111. https://doi.org/10.1111/aogs.14428

Hayes, T. B., Khoury, V., Narayan, A., Gallipeau, M. H., Manzanarez, T., Porter, R., & Johnston, G. (2011). Demasculinization and feminization of male gonads by atrazine: Consistent effects across vertebrate classes. Journal of Steroid Biochemistry and Molecular Biology, 127(1–2), 64–73. doi: 10.1016/j.jsbmb.2011.03.015.

Hembree, W. C., Cohen-Kettenis, P. T., Gooren, L., Hannema, S. E., Meyer, W. J., Murad, M. H., Rosenthal, S. M., Safer, J. D., Tangpricha, V., & T'Sjoen, G. G. (2017). Endocrine treatment of gender-dysphoric/gender-incongruent persons: An Endocrine Society clinical practice guideline. The Journal of Clinical Endocrinology & Metabolism, 102(11), 3869–3903. https://doi.org/10.1210/jc.2017-01658

Huerta-Fontela, M., Galceran, M. T., & Ventura, F. (2011). Occurrence and removal of pharmaceuticals and hormones through drinking water treatment. Water Research, 45(7), 2218–2228. https://doi.org/10.1016/j.watres.2010.10.036

Iftikhar, N., Zafar, R., & Hashmi, I. (2022). Multi-biomarkers approach to determine the toxicological impacts of sulfamethoxazole antibiotic on freshwater fish Cyprinus carpio. Ecotoxicology and Environmental Safety, 233, 113331. https://doi.org/10.1016/j.ecoenv.2022.113331

Itzel, F., Jewell, K. S., Leonhardt, J., Gehrmann, L., Nielsen, U., Ternes, T. A., Schmidt, T. C., & Tuerk, J. (2018). Comprehensive analysis of antagonistic endocrine activity during ozone treatment of hospital wastewater. Science of the Total Environment, 624, 1443–1454. https://doi.org/10.1016/j.scitotenv.2017.12.181

Jablonowski, N. D., Schäffer, A., & Burauel, P. (2011). Still present after all these years: Persistence of atrazine in the environment. Environmental Science and Pollution Research, 18(3), 328–331. doi: 10.1007/s11356-010-0431-y

Jantzen, C. E., Toor, F., Annunziato, K. A., & Cooper, K. R. (2017). Effects of chronic perfluorooctanoic acid (PFOA) at low concentration on morphometrics, gene expression, and fecundity in zebrafish (Danio rerio). Reproductive Toxicology, 69, 34–42. https://doi.org/10.1016/j.reprotox.2017.01.009

Johnson, A. C., & Sumpter, J. P. (2001). Removal of endocrine-disrupting chemicals in activated sludge treatment works. Environmental Science & Technology, 35(24), 4697–4703. https://doi.org/10.1021/es010171j

Karthikraj, R., Vasu, A. K., Balakrishna, K., Sinha, R. K., & Kannan, K. (2017). Occurrence and fate of parabens and their metabolites in five sewage treatment plants in India. Science of the Total Environment, 593–594, 592–598. https://doi.org/10.1016/j.scitotenv.2017.03.173

Kidd, K. A., Blanchfield, P. J., Mills, K. H., Palace, V. P., Evans, R. E., Lazorchak, J. M., & Flick, R. W. (2007). Collapse of a fish population after exposure to a synthetic estrogen. Proceedings of the National Academy of Sciences of the United States of America, 104(21), 8897–8901. https://doi.org/10.1073/pnas.0609568104

Kim, M.-K., & Zoh, K.-D. (2016). Occurrence and removals of micropollutants in water environment. Environmental Engineering Research, 21(4), 319–332. https://doi.org/10.4491/eer.2016.115

Kristensen, D. M., Desdoits-Lethimonier, C., Mackey, A. L., Dalgaard, M. D., De Masi, F., Munkbøl, C. H., Styrishave, B., Antignac, J.-P., Le Bizec, B., Platel, C., Hay-Schmidt, A., Jensen, T. K., Lesné, L., Mazaud-Guittot, S., Kristiansen, K., Brunak, S., Kjær, M., Juul, A. C., & Jégou, B. (2018). Ibuprofen alters human testicular physiology to produce a state of compensated hypogonadism. Proceedings of the National Academy of Sciences of the United States of America, 115(4), e715–e724. https://doi.org/10.1073/pnas.1715035115

Luo, Y., Guo, W., Ngo, H. H., Nghiem, L. D., Hai, F. I., Zhang, J., Liang, S., & Wang, X.-C. (2014). A review on the occurrence of micropollutants in the aquatic environment and their fate and removal during wastewater treatment. Science of the Total Environment, 473–474, 619–641. https://doi.org/10.1016/j.scitotenv.2013.12.065

Madikizela, L. M., & Chimuka, L. (2017). Occurrence of naproxen, ibuprofen and diclofenac residues in wastewater and river water of KwaZulu-Natal

Province in South Africa. Environmental Monitoring and Assessment, 189(7), 348. https://doi.org/10.1007/s10661-017-6069-1

Margot, J., Kienle, C., Magnet, A., Weil, M., Rossi, L., de Alencastro, L. F., Abegglen, C., Thonney, D., Chèvre, N., Schärer, M., & Barry, D. A. (2013). Treatment of micropollutants in municipal wastewater: Ozone or powdered activated carbon? Science of the Total Environment, 461-462, 480–498. https://doi.org/10.1016/j.scitotenv.2013.05.034

Mechoulam, R., Brueggemeier, R. W., & Denlinger, D. L. (1984). Estrogens in insects. Cellular and Molecular Life Sciences, 40, 942–944. https://doi.org/10.1007/BF01946450

Muñoz-de-Toro, M., Markey, C. M., Wadia, P. R., Luque, E. H., Rubin, B. S., Sonnenschein, C., & Soto, A. M. (2005). Perinatal exposure to bisphenol-A alters peripubertal mammary gland development in mice. Endocrinology, 146(9), 4138–4147. https://doi.org/10.1210/en.2005-0340

National Center for Biotechnology Information. (2025). Sulfamethoxazole – Substance summary. PubChem, National Library of Medicine, National Institutes of Health. https://pubchem.ncbi.nlm.nih.gov/compound/Sulfamethoxazole

Nevitt, S. J., Marson, A. G., Weston, J., & Tudur Smith, C. (2016). Phenytoin versus valproate monotherapy for partial onset seizures and generalised onset tonic-clonic seizures: An individual participant data review. Cochrane Database of Systematic Reviews, 2016(4), Article CD001769. https://doi.org/10.1002/14651858.CD001769.pub3

Nevitt, S. J., Marson, A. G., Weston, J., & Tudur Smith, C. (2017). Carbamazepine versus phenytoin monotherapy for epilepsy: An individual participant data review. Cochrane Database of Systematic Reviews, 2017(2), Article CD001911. https://doi.org/10.1002/14651858.CD001911.pub3

Nicole, W. (2013). PFOA and cancer in a highly exposed community: New findings from the C8 science panel. Environmental Health Perspectives, 121(11-12), A340. https://doi.org/10.1289/ehp.121-A340

Nowak, K., Jabłońska, E., & Ratajczak-Wrona, W. (2021). Controversy around parabens: Alternative strategies for preservative use in cosmetics and personal care products. Environmental Research, 198, 110488. https://doi.org/10.1016/j.envres.2020.110488

Patrolecco, L., Rauseo, J., Ademollo, N., Grenni, P., Cardoni, M., Levantesi, C., Luprano, M. L., & Barra Caracciolo, A. (2018). Persistence of the antibiotic sulfamethoxazole in river water alone or in the co-presence of ciprofloxacin. Science of the Total Environment, 640–641, 1438–1446. https://doi.org/10.1016/j.scitotenv.2018.06.025

Petrie, B., Barden, R., & Kasprzyk-Hordern, B. (2015). A review on emerging contaminants in wastewaters and the environment: Current knowledge, understudied areas and recommendations for future monitoring. Water Research, 72, 3–27. https://doi.org/10.1016/j.watres.2014.08.053

Praskova, E., Plhalova, L., Chromcova, L., Stepanova, S., Bedanova, I., Blahova, J., Hostovsky, M., Skoric, M., Maršálek, P., Voslarova, E., & Svobodova, Z. (2014). Effects of subchronic exposure of diclofenac on growth, histopathological changes, and oxidative stress in zebrafish (Danio rerio). The Scientific World Journal, 2014, 645737. https://doi.org/10.1155/2014/645737

Rochman, C. M., Kurobe, T., Flores, I., & Teh, S. J. (2014). Early warning signs of endocrine disruption in adult fish from the ingestion of polyethylene with and without sorbed chemical pollutants from the marine environment. Science of the Total Environment, 493, 656–661. https://doi.org/10.1016/j.scitotenv.2014.06.051

Rogowska, J., Cieszynska-Semenowicz, M., Ratajczyk, W., & Wolska, L. (2020). Micropollutants in treated wastewater. Ambio, 49(2), 487–503. https://doi.org/10.1007/s13280-019-01219-5

Roth, L., Adler, M., Jain, T., & Bempong, D. (2018). Monographs for medicines on WHO’s Model List of Essential Medicines. Bulletin of the World Health Organization, 96(6), 378–385. https://doi.org/10.2471/BLT.17.205807

Rudel, R. A., Fenton, S. E., Ackerman, J. M., Euling, S. Y., & Makris, S. L. (2011). Environmental exposures and mammary gland development: State of the science, public health implications, and research recommendations. Environmental Health Perspectives, 119(8), 1053–1061. https://doi.org/10.1289/ehp.1002864

Saldanha, C. J., Remage-Healey, L., & Schlinger, B. A. (2011). Synaptocrine signaling: Steroid synthesis and action at the synapse. Endocrine Reviews, 32(4), 532–549. https://doi.org/10.1210/er.2011-0004

Santen, R. J., & Simpson, E. (2019). History of estrogen: Its purification, structure, synthesis, biologic actions, and clinical implications. Endocrinology, 160(3), 605–625. https://doi.org/10.1210/en.2018-00529

Schönfelder, G., Wittfoht, W., Hopp, H., Talsness, C. E., Paul, M., & Chahoud, I. (2002). Parent bisphenol A accumulation in the human maternal-fetal-placental unit. Environmental Health Perspectives, 110(11), A703–A707. https://doi.org/10.1289/ehp.110-1241091

Simpson, E. R., & Davis, S. R. (2001). Minireview: Aromatase and the regulation of estrogen biosynthesis — Some new perspectives. Endocrinology, 142(11), 4589–4594. https://doi.org/10.1210/endo.142.11.8547

Snyder, S. A., Westerhoff, P., Yoon, Y., & Sedlak, D. L. (2003). Pharmaceuticals, personal care products, and endocrine disruptors in water: Implications for the water industry. Environmental Engineering Science, 20(5), 449–469.https://doi.org/10.1089/109287503768335931

Staples, C. A., Dorn, P. B., Klecka, G. M., O'Block, S. T., & Harris, L. R. (1998). A review of the environmental fate, effects, and exposures of bisphenol A. Chemosphere, 36(10), 2149–2173. https://doi.org/10.1016/S0045-6535(97)10133-3

Sunderland, E. M., Hu, X. C., Dassuncao, C., Tokranov, A. K., Wagner, C. C., & Allen, J. G. (2019). A review of the pathways of human exposure to poly- and perfluoroalkyl substances (PFASs) and present understanding of health effects. Journal of Exposure Science & Environmental Epidemiology, 29(2), 131–147. https://doi.org/10.1038/s41370-018-0094-1

Swan, G. E., Naidoo, V., Cuthbert, R., Green, R. E., Pain, D. J., Swarup, D., Prakash, V., Taggart, M., Bekker, L., Das, D., Diekmann, J., Diekmann, M., Killian, E., Meharg, A., Patra, R. C., Saini, M., & Wolter, K. (2006). Removing the threat of diclofenac to critically endangered Asian vultures. PLoS Biology, 4(3), e66. https://doi.org/10.1371/journal.pbio.0040066

United States Environmental Protection Agency. (2025). Atrazine: Overview. Retrieved from: https://www.epa.gov/ingredients-used-pesticide-products/atrazine

Verlicchi, P., Galletti, A., Petrovic, M., & Barceló, D. (2010). Hospital effluents as a source of emerging pollutants: An overview of micropollutants and sustainable treatment options. Journal of Hydrology, 389(3–4), 416–428. https://doi.org/10.1016/j.jhydrol.2010.06.005

Wang, Y., Wang, Q., Hu, L., Lu, G., & Li, Y. (2015). Occurrence of estrogens in water, sediment and biota and their ecological risk in Northern Taihu Lake in China. Environmental Geochemistry and Health, 37(1), 147–156. https://doi.org/10.1007/s10653-014-9637-0

Zhang, Y., Xiu, W., Yan, M., Guo, X., Ni, Z., Gu, J., Tang, T., & Liu, F. (2023). Adverse effects of sulfamethoxazole on locomotor behavior and lipid metabolism by inhibiting acetylcholinesterase and lipase in Daphnia magna. Science of the Total Environment, 892, 164631. https://doi.org/10.1016/j.scitotenv.2023.164631

CHAPTER 2

Detection of Application Layer Attacks: A Survey of Machine Learning and Deep Learning Methods

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1. Introduction

In the digital world, web applications are immensely popular in the society. This popularity has increased the number of threats and attacks targeting web applications and has raised concerns regarding security. The attacks are often carried out in a strategic and profitable way by malicious actors, commonly referred to as hackers. As part of these strategies, hackers target web applications based on their objectives, methods, attack types, and chosen targets. The targets may span multiple attack surfaces, ranging from the network layer to the application layer. Accordingly, different attack surfaces require different attack techniques and may result in different types of harm to the targets. For example, attacks targeting the network layer often aim to disrupt communication between the server and the user, or to intercept and obtain information from the network communication channel between them (e.g., Man-in-the-Middle attacks).

Such web attacks require logging, monitoring, quick response, and effective defense by authorities. However, human involvement in response and defense is inherently limited by factors such as the need for rest, sleep and fixed working hours. Hackers often exploit these limitations by launching attacks during late or off-work hours, increasing the potential damage to the targets. In this context, Artificial Intelligence (AI) emerges as a valuable supportive security measure, enabling automated detection of attacks and helping to reduce their impact.

In particular, machine and deep learning-based techniques have been studied for application-layer attack detection. However, the literature on application-layer attack detection largely focuses on attacks such as application-layer distributed denial-of-service (DDoS) and other commonly researched attacks like cross-site scripting (XSS), while server-side request forgery (SSRF) attacks have received comparatively less attention.

Motivated by this gap, this study surveys recent machine and deep learning-based approaches for detecting representative application-layer attacks, which are SQL injection (SQLi), XSS, and SSRF, thereby providing a more balanced overview of application-layer attack detection.

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In addition, it is important to document the relevance of these attacks. The Open Web Application Security Project (OWASP) Top Ten 2025 is the current list published by the OWASP Foundation to raise awareness of critical security risks affecting web applications, with risks ranked based on factors such as impact and frequency. In this list, SQLi and XSS are placed under A05:2025 - Injection, whereas SSRF does not have a direct category but may be associated with broader categories such as A06:2025 - Insecure Design or, more specifically, A10:2025 - Mishandling of Exceptional Conditions (OWASP Foundation, 2025). Compared to the OWASP Top Ten 2021, where injection attacks were ranked as A03:2021 and SSRF appeared as a separate category (A10:2021 - Server-Side Request Forgery), these changes show the evolving nature of web application security risks and highlight the continued need for effective detection and prevention approaches (OWASP Foundation, 2021).

Given the relevance of these attacks, the following section briefly provides background on the application layer and the attacks considered in this survey.

2. Application Layer and Attacks Considered in This Survey

This section provided an overview of the application layer and four representative application-layer attacks considered in this survey. These attacks were considered as representative examples since they reflect application layer behaviors and are addressed using various detection approaches.

The application layer is the highest layer of the Open Systems Interconnection (OSI) model and is the layer in which applications interact with end users. In the context of web applications, this layer supports application-level communication and processes user requests and responses. Common protocols such as Domain Name System (DNS), Hypertext Transfer Protocol Secure (HTTPS), and Simple Mail Transfer Protocol (SMTP) operate at this layer (Kumar et al., 2014). Due to its interaction with end users and the data it processes, hackers often target this layer.

As a result, several attack types specifically target the application layer. Table 1 summarizes the representative application-layer attacks considered in this survey, including their names, definitions, and technique categories (e.g., injection). By doing so, the table provides background information on the attacks considered and supports the understanding of the detection approaches discussed in the following sections.

Table 1: Representative attacks, their definitions, and technique categories

Attack	Definition	Technique Category
SQLi	Malicious SQL statements injected through user-input fields that may be executed by the database or web server (Borana et al., 2024)	Injection
XSS	Malicious client-side scripts (e.g., JavaScript) injected into web pages that may be executed in the user's browser (Samo et al., 2024)	Injection
SSRF	Malicious requests are redirected by the server to the internal network, which may expose internal or local services (Jabiyet et al., 2021)	Server Request Abuse

As can be seen in Table 1, the representative attacks include both malicious scripts and server-directed requests, and they may lead to the leakage of confidential data. Furthermore, these attacks vary in their techniques, as they involve not only injection but also server-side request abuse. Injection attacks involve inserting malicious input through web application inputs, whereas server-side request abuse involves tricking the server into making requests on the hacker's behalf. These diverse techniques highlight the importance of secure software design and development practices, as well as proper server configurations.

3. Recent Detection Studies for Representative Attacks

This section included two main subsections reviewing recent machine learning-based and deep learning-based studies published between 2023 and 2026, covering literature available up to February 16, 2026, and addressing the attack types considered in this survey (SQLi, XSS, and SSRF). The reviewed studies were primarily identified through Google Scholar, with additional sources from academic databases such as SpringerLink. They were summarized in terms of attack type, detection approach, employed models, datasets, feature selection methods, and reported performance.

3.1. Machine Learning-Based Studies

The following studies present machine learning approaches for detecting SQLi, XSS, and SSRF attacks.

3.1.1. SQLi Detection in Machine Learning-Based Studies

One study by Arasteh et al. (2026) presented an SQL injection detection method that combines heuristic-driven feature selection using the Binary Whale Optimization Algorithm (BWOA) with machine learning classifiers, including artificial neural networks (ANN), support vector machines (SVM), decision trees (DT), and k-nearest neighbor (KNN). The detection approach follows a supervised classification setting and is evaluated experimentally. The dataset was created using SQL Query Profiler and it consists of 1027 SQL query entries, including 473 normal and 554 malicious samples. The authors report improved detection performance after feature selection with BWOA, highlighting the effectiveness of the method under the considered setting.

Another study by Rosca et al. (2025) proposed a machine learning-based model including a novel element that is a two-stage personalized software processing pipeline. The dataset in the study was constructed using synthetic data, generated with the GPT-4 model (version GPT-4o), in combination with a public Kaggle dataset titled “SQL-Injection-Extend dataset”. The GPT-4o model generated 72,304 malicious queries, while the relevant Kaggle public dataset included 17,695 legitimate queries. The data was processed within a pipeline that the authors proposed, consisting of two stages, namely syntactic normalization and the extraction of eight semantic features for model training. The processed data were used to train and evaluate several machine learning models implemented using the Azure Machine Learning Studio platform, combined with different sampling strategies for dataset partitioning. Among the evaluated models, the Voting Ensemble model achieved the best performance, reaching an accuracy of 96.86%, a weighted AUC of 98.25%, and a weighted F1-score of 96.77%. The Voting Ensemble model consisted of a weighted combination of boosting-based classifiers, dominantly based on eXtreme Gradient Boosting (XGBoost) and complemented by LightGBM, which contributed to the improved classification performance. The results demonstrate the effectiveness of the proposed pipeline in transforming raw SQL queries into meaningful features for classification and highlight its potential integration as an additional security layer in web application architectures.

Mahmood, S. S. (2025) also proposed an advanced machine learning-based approach for enhancing SQLi detection by evaluating SVM, XGBoost, and ensemble learning techniques. The data was collected from two Kaggle public datasets titled “Modified SQL Dataset” and “SQLv2”. The data was preprocessed by cleaning and transforming it into a structured numerical representation using Term Frequency-Inverse Document Frequency (TF-IDF), and additionally, an n-gram analysis was carried out to capture sequential dependencies between words. Upon preprocessing and feature extraction, the dataset in the study was split into 80% for training and 20% for testing. Several classification models were evaluated, including DT, random forest (RF), gradient boosting (GB), extra trees (ET), and multi-layer perceptron (MLP), in addition to ensemble methods such as stacking and soft voting. Among the evaluated approaches, the stacking ensemble demonstrated the best overall performance by combining the strengths of multiple classifiers. The study also incorporated Local Interpretable Model-agnostic Explanations (LIME) to improve model interpretability by identifying the key features influencing classification decisions. The results indicate that ensemble learning techniques improve SQLi detection performance and provide a more robust and interpretable detection framework.

The following subsection presents machine learning-based approaches for XSS attacks.

3.1.2. XSS Detection in Machine Learning-Based Studies

In a very recent study, Qasim et al. (2026) proposed a hybrid supervised-unsupervised machine learning-based approach with context-aware (URL, HTML, JS) features for XSS detection and behavioral classification. The proposed approach integrated context-aware feature extraction with supervised binary detection and unsupervised clustering for enabling accurate XSS detection, latent attack discovery, and interpretable analysis within a unified pipeline. The dataset used in the study was titled "Fawaz2015 XSS dataset", including both malicious and benign web payloads. The data was first preprocessed through normalization and decoding procedures to improve feature consistency, after which context-aware features were extracted, resulting in a 66-dimensional feature representation. The supervised detection stage used a Random Forest (RF) classifier to distinguish malicious from benign samples, while the unsupervised stage applied K-Means clustering to discover behavioral patterns of XSS attacks, including reflected, stored, and DOM-based categories without relying on explicit multi-class labels. The framework also incorporated feature standardization and model interpretability analysis to explain classification decisions. The experimental results demonstrated high detection performance and showed that the proposed hybrid framework improves detection accuracy while enabling meaningful behavioral classification of XSS attacks, highlighting its applicability for practical web security environments.

Gharai et al. (2025) indicated the primary objective of the study as classifying XSS attacks that categorize XSS payloads into three groups, which are reflected, stored, and DOM-based. A benchmark dataset from the IEEE Dataport repository is utilized for model training and testing, consisting of 74,062 URL-encoded samples. The dataset was preprocessed through decoding and normalization procedures, followed by tokenization and TF-IDF feature extraction to generate structured feature representations. The authors criticized the feature selection techniques of prior studies and applied some of the most used machine learning-based algorithms, which are Random Forest (RF), Decision Tree (DT), K-Nearest Neighbors (KNN), and Support Vector Classifier (SVC), which is SVM's specific application for solely classification problems. The authors reported RF with the feature selection method named Recursive Feature Elimination (RFE) to have the highest accuracy score of 0.9789.

Bacha et al. (2024) introduced a novel hybrid ensemble learning framework for XSS that utilizes a combination of machine learning-based models, which are Logistic Regression (LR), Support Vector Machine (SVM), XGBoost, Categorical Boosting (CatBoost), and Deep Neural Networks (DNN). The proposed framework used a stacking ensemble approach in which multiple base models were combined through a meta-classifier to improve detection performance. The authors used the dataset named XSS-Attacks-2021, which includes 460 samples. The data was preprocessed through handling missing values, encoding categorical variables, and normalization. Additionally, Principal Component Analysis (PCA) was applied for dimensionality reduction, and Synthetic Minority Oversampling Technique (SMOTE) was used to address class imbalance. The authors reported that false positives and false negatives were effectively minimized due to the feature engineering and model tuning approaches used in the study. It is also reported that the accuracy of the proposed model was 99.87%.

Thaipakdee et al. (2025) presented a novel model named SMARTX that utilizes a machine learning-based approach that is Multilayer Perceptron (MLP) for XSS attack classification. The authors made use of two text-based dataset files named XSS_20000_Line.txt and Non_XSS_180000.txt. As their name already suggests, the dataset file XSS_20000_Line.txt included XSS attack data with 20,000 samples, while the dataset file named Non_XSS_180000.txt included non-XSS data with 180,000 samples. The input data were preprocessed through feature extraction techniques including TF-IDF and URL-based feature analysis to generate structured representations. Due to the class imbalance in datasets, the authors utilized Synthetic Minority Oversampling Technique (SMOTE). The proposed SMARTX model also employed multiprocessing techniques to enable real-time threat analysis and used a graph-based database (Neo4j) to store and visualize detection results across web applications. The proposed SMARTX model had an accuracy score of 98.43% and a false positive rate on Non-XSS of 1.83%. The authors concluded that this model is suitable for real-time detection in high-traffic web applications.

In the following subsection, machine learning-based approaches for SSRF attacks are presented.

3.1.3. SSRF Detection in Machine Learning-Based Studies

The literature review revealed that recent studies on SSRF detection are relatively limited compared to SQLi and XSS. This difference might be related to the distinct nature of SSRF attacks, which involve server-side request abuse rather than direct input injection, as well as the limited availability of datasets and real-world evaluation environments. Although SSRF remains a relevant web application vulnerability, only two recent studies were identified and included in this subsection.

Kumthe (2024), although not solely a machine learning-based study, developed a hybrid detection model that combines traditional machine learning and deep learning techniques for binary classification (attack vs. non-attack). The proposed approach integrated Random Forest (RF) with Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. The study utilized the CIC-Bell-DNS 2021 dataset published by the Canadian Institute for Cybersecurity, which provides both legitimate and malicious DNS traffic data. Unlike some of the previously discussed studies, this dataset originates from an official and publicly available source. Due to class imbalance in the dataset, SMOTE was employed, while Chi-square (Chi^2) was used for feature selection. The results showed that the RF model achieved a high accuracy of 98.41%, demonstrating its effectiveness in detecting SSRF attacks.

Quiroz et al. (2025) developed a machine learning-based approach for detecting Server-Side Request Forgery (SSRF) vulnerabilities through web traffic analysis. The study used a synthetic dataset consisting of 15,000 samples distributed across 15 classes representing different SSRF scenarios along with legitimate traffic. The dataset was divided into 70% for training and 30% for testing. The authors evaluated several machine learning algorithms, including RF, XGBoost, Light Gradient Boosting Machine (LightGBM), LR, DT, Extra Trees (ET), and ensemble methods such as Voting and Stacking classifiers. The results showed that tree-based models achieved the highest performance, with an accuracy of approximately 96%, and demonstrated the effectiveness of machine learning techniques for SSRF detection.

With this subsection, the machine learning-based approaches identified in recent studies have been reviewed. The following subsection focuses on deep learning-based approaches.

3.2. Deep Learning-Based Studies

Following the structure of Section 3.1, the following studies present deep learning approaches for detecting SQLi, XSS, and SSRF attacks.

3.2.1 SQLi Detection in Deep Learning-Based Studies

Sun et al. (2023) reviewed existing SQLi detection approaches, including machine learning-based methods, and noted that many studies mainly focus on feature extraction, while detection performance often depends on the quality of manually designed features. The authors also pointed out that traditional and some AI-based detection approaches may suffer from high false positive and false negative rates. There were six datasets named DS1-DS6, each containing 50,370 benign samples, while the number of SQL injection samples increased progressively from 10,052 to 60,052, resulting in different positive-to-negative sample ratios. In their study, they proposed a deep learning-based model for SQLi detection that combines an improved TextCNN and Bidirectional LSTM (Bi-LSTM) architecture with an attention mechanism. The proposed system consists of two phases: offline training and online testing. For feature representation, the authors used TF-IDF and Word2Vec, and also BERT-based representations. Their results showed that the model improved SQLi detection performance and reduced false positive and false negative rates.

Alghawazi et al. (2023) proposed an architecture that utilizes a Recurrent Neural Network (RNN) autoencoder model and compared this architecture with several existing machine learning-based models, including DT, SVM, RF, LR, ANN, CNN, and Naive Bayes. The proposed architecture was trained using a publicly available Kaggle dataset named “sql-injection-dataset”, which consisted of 30,907 SQL query records, including 11,378 malicious SQLi samples and 19,529 benign samples. The data were preprocessed through cleaning procedures, including the removal of null values and duplicate records, and the dataset was divided into two parts: 80% for training and 20% for testing. The proposed model achieved the best performance when trained for 50 epochs using the Adam optimizer. The authors evaluated the model using performance metrics including accuracy, precision, recall, and F1-score, and reported that the proposed RNN autoencoder outperformed the machine learning-based models, achieving an accuracy of 94% and an F1-score of 92%.

Kakisim (2024) introduced a deep learning-based SQL injection detection system called Bidirectional LSTM–CNN based on Multi-View Consensus (MVC-BiCNN). The proposed method used a hybrid architecture that combined bidirectional long short-term memory (BiLSTM) and convolutional neural network (CNN) layers to capture sequential dependencies and local features in SQL queries. The system applied a preprocessing phase that generated multiple representations of SQL inputs through tokenization, semantic SQL tag extraction, and enriched representations using semantic encoding. The author used multiple publicly available datasets from GitHub and Kaggle. The datasets were combined after removing duplicate samples and adding legitimate queries to construct a final dataset containing 20,002 malicious SQLi samples and 29,379 benign samples. The data were divided into 80% for training and 20% for testing, and fivefold cross-validation was applied. The model was evaluated using performance metrics including accuracy, false positive rate, and false negative rate. The experimental results showed that the proposed MVC-BiCNN model achieved a detection rate of 99.96% and outperformed baseline machine learning and deep learning models.

Smrity et al. (2025) proposed a deep learning-based SQL injection detection model called SQLGuardNet. The authors used three publicly available datasets from Kaggle, where 0 represented non-malicious queries and 1 represented SQLi scripts. The datasets differed in size: dataset 1 contained 19,537 benign and 19,537 malicious queries, dataset 2 contained 77,750 benign and 77,750 malicious queries, and dataset 3 contained 81,719 benign and 81,719 malicious queries. The data were preprocessed by removing null values and duplicates, converting queries to lowercase, and applying tokenization and TF-IDF weighting, and were divided into training, validation, and testing sets. The proposed model followed a multi-branch architecture consisting of three branches: a Transformer block with multi-head attention, a one-dimensional convolutional layer, and an RNN with LSTM units. Each branch processed the input separately and the outputs were combined using a concatenation layer. The authors reported that each branch improved detection performance. The proposed model achieved high accuracy rates of 99.89%, 99.10%, and 99.12% for datasets 1, 2, and 3 accordingly, and a soft voting mechanism that combined SQLGuardNet with other deep learning models further improved binary classification performance.

3.2.2. XSS Detection in Deep Learning-Based Studies

Et-tolba et al. (2024) proposed a deep learning-based XSS detection model using an LSTM neural network combined with an attention mechanism and Word2Vec embeddings. The study used two public datasets containing HTTP request data, where the first dataset included 7,373 normal and 6,313 malicious samples, and the second dataset contained 31,407 normal and 33,426 malicious samples. The data were preprocessed through cleaning, decoding, and tokenization procedures, and word embedding techniques were applied to convert input sequences into numerical vectors. The proposed model used an embedding layer, bidirectional LSTM layers, and an attention mechanism to capture contextual patterns in XSS payloads. The results showed high detection performance, achieving accuracy values of 99.56% and 99.11% on the two datasets.

Luu et al. (2025) proposed a framework that constructed a novel dataset for cross-site scripting (XSS) detection by automatically collecting web resources and extracting informative features. The constructed dataset consisted of 107,406 samples, including 90,918 benign and 16,488 malicious scripts. The proposed framework, named XSShield, used a deep learning model that combined CNN and LSTM architectures to capture both local and sequential patterns in web inputs. The data were processed through feature extraction and preprocessing steps before model training. The authors evaluated the model using performance metrics including accuracy and false positive rate. The experimental results showed a high accuracy rate of 99.27%, a low false positive rate of 0.06%, and a processing rate exceeding 1000 samples per second.

Li et al. (2025) proposed a hybrid deep learning-based model that integrates CNN and Bidirectional LSTM (BiLSTM) networks with an attention mechanism for XSS detection. The study utilized two publicly available datasets, XSSed-DMOZ and Merwani-XSS, containing 64,833 samples (31,407 benign and 33,426 malicious) and 42,664 samples (27,675 benign and 14,989 malicious), respectively. The data were preprocessed through normalization and tokenization, and word embedding techniques were applied to represent input payloads numerically. The CNN component was used to capture local features, while the BiLSTM layer modeled sequential dependencies, and the attention mechanism improved feature importance learning. The CNN-BiLSTM-Attention architecture achieved the highest accuracy and F1-score among the evaluated models on both datasets. The study further demonstrated that removing the CNN, BiLSTM, or attention component led to lower performance, suggesting that all components play an important role in detection.

3.2.3. SSRF Detection in Deep Learning-Based Studies

Mukamisha et al. (2025a) conducted an empirical analysis of deep learning-based approaches for SSRF detection by evaluating LSTM and BERT models using the CIC-URL2016 dataset. The dataset contained 15,711 labeled URL samples, including 7,930 malicious and 7,781 benign instances. After preprocessing and feature extraction, the models were trained and evaluated to assess their effectiveness in detecting SSRF attacks. The results showed that the LSTM model achieved a detection accuracy of 98.2%, outperforming the BERT model (94%). The authors highlighted the effectiveness of LSTM in capturing sequential URL patterns for SSRF detection and noted that deep learning-based models require significant computational resources during training.

In a follow-up study, Mukamisha et al. (2025b) expanded their analysis by benchmarking multiple deep learning architectures for SSRF detection, including LSTM, BiLSTM, GRU, and BERT. Using the same CIC-URL2016 dataset consisting of 15,711 labeled URL samples (7,930 malicious and 7,781 benign), the models were evaluated under identical experimental conditions using five-fold cross-validation. The results indicated that the GRU model achieved the highest performance, reaching an average accuracy of 99.83%, followed by BiLSTM and LSTM, while BERT demonstrated comparatively lower performance. The authors also analyzed computational efficiency and suggested a hybrid deployment strategy in which GRU could be used for real-time detection while BERT could support deeper offline analysis.

4. Discussion

4.1. General Patterns in Machine Learning-Based Studies

In this subsection, the general patterns in machine learning-based studies are discussed.

To better identify general patterns among the reviewed machine learning-based studies, Table 2 presented a comparative summary of each study in terms of attack, dataset, model(s), feature engineering method, key findings, and reported novelty. For brevity, the following abbreviations are used in the table: feature engineering method (F.E.M.), key findings (K.F.), and reported novelty (R.N.).

Table 2. Summary of Recent Machine Learning-Based Studies

Study	Attack	Dataset (Total | Benign / Attack)	Model(s)	F.E.M.	K.F.	R.N.
Arasteh et al. (2026)	SQLi	Author-constructed dataset (1027 | 473 / 554)	SVM, DT, KNN, ANN	BWOA	BWOA improved detection and classification accuracy	BWOA-based F.E.M.
Rosca et al. (2025)	SQLi	GPT-4o (synthetic) + SQL-Injection-Extend (Kaggle) (90,000 | 17,695 / 72,304)	RF, ET, XGBoost, LR, LightGBM, Voting Ensemble	Syntactic normalization and semantic feature extraction	Feature extraction pipeline enhanced detection accuracy	Two-stage feature extraction pipeline
Mahmood S.S. (2025)	SQLi	Modified SQL Dataset + SQLv2 (Kaggle) (Not reported)	DT, RF, GB, ET, MLP, ensemble methods (stacking and soft voting)	TF-IDF and n-gram feature extraction	TF-IDF features with ensemble models enhanced detection	Stacking ensemble framework
Qasim et al. (2026)	XSS	Fawaz2015 XSS (138,569 | 100,000 / 38,569)	RF classifier and K-Means clustering	Context-aware feature extraction (URL, HTML, JS)	Hybrid RF–K-Means framework improved detection and enabled behavioral attack classification	Hybrid context-aware detection framework
Gharai et al. (2025)	XSS	IEEE Dataport XSS dataset (74,062 | Size not reported)	RF, DT, KNN, SVC (SVM)	TF-IDF Feature Extraction and Recursive Feature Elimination (RFE)	RF with RFE achieved highest detection accuracy (97.9%)	RFE-based feature selection for multi-class XSS classification
Bacha et al. (2024)	XSS	XSS-Attacks-2021 dataset (460 | Size not reported)	LR, SVM, XGBoost, CatBoost, DNN (stacking ensemble)	PCA + SMOTE	Hybrid ensemble detection accuracy (99.87%) with low FP/FN	Hybrid ensemble XSS detection framework
Thaipakdee et al. (2025)	XSS	XSS_20000_Line and Non_XSS_180000	MLP (SMARTX Model)	TF-IDF + URL-based feature extraction	SMARTX achieved 98.43% detection	SMARTX real-time XSS

		datasets (200000 | 20,000 / 180,000)			accuracy with low FP	detection framework
Kumthe (2024)	SSRF	CIC-Bell-DNS 2021 (Size not reported)	RF, CNN-LSTM	Chi^2 + SMOTE	CNN-LSTM achieved highest detection accuracy (99.65%)	Hybrid CNN-LSTM SSRF detection model
Quiroz et al. (2025)	SSRF	Synthetic Dataset (15,000 | Size not reported)	RF, XGBoost, LightGBM, LR, DT, ET, Voting and Stacking Ensembles	HTTP request feature extraction + normalization + encoding	RF, XGBoost and LightGBM showed best detection accuracy with 96%	Multi-class SSRF detection

techniques, particularly TF-IDF-based methods, highlighting the importance of feature extraction and feature selection for attack detection performance. This frequent use of TF-IDF-based feature extraction could be attributed to its effectiveness in representing text-based attack payloads, such as malicious SQL queries or JavaScript code used in XSS attacks.

On the other hand, another recurring trend is the adoption of hybrid or ensemble learning approaches (e.g., Rosca et al., 2025; Mahmood S.S., 2025; Bacha et al., 2024), indicating that performance improvements are commonly achieved through model combination rather than relying on a single model.

Another noticeable pattern can be seen in the dataset types commonly used in recent machine learning-based studies. Many studies, such as Qasim et al. (2026), relied on publicly available datasets obtained from open repositories such as Kaggle and GitHub, which provide collections of payloads or URLs for training detection models. However, fewer datasets came from established Cyber Security research institutions, such as those provided by the Canadian Institute for Cybersecurity (CIC). For example, the CIC-Bell-DNS 2021 dataset was used by Kumthe (2024) for SSRF attack detection. This situation may reflect the limited availability of real-world cyber security datasets.

In addition, some recent studies, such as Rosca et al. (2025), have generated synthetic datasets using AI tools, including large language models such as GPT-based systems, to expand existing datasets and simulate malicious inputs. While AI-generated synthetic data may help address data scarcity and class imbalance, it may not fully represent real-world attack behavior, which could affect how well detection models perform in real-world environments.

Similarly, some studies addressed dataset imbalance using SMOTE, as observed in Bacha et al. (2024) and Kumthe (2024). While this approach helped reduce class imbalance and model bias toward the majority class, it relied on artificially generated samples, which may further reflect the limitations of available real-world cybersecurity datasets.

Overall, these patterns suggested that recent machine learning-based application-layer attack detection research mainly focused on improving detection performance through feature engineering techniques, particularly TF-IDF-based feature extraction, and hybrid or ensemble model integration.

4.2. General Patterns in Deep Learning-Based Studies

In this subsection, similar to the previous section, the general patterns in deep learning-based studies are discussed, and Table 3 provided a summary of recent deep learning-based studies. For brevity, the following abbreviations are used in the table: key findings (K.F.) and reported novelty (R.N.).

Table 3. Summary of Recent Deep Learning-Based Studies

Study	Attack	Dataset (Total | Benign / Attack)	Model(s)	K.F.	R.N.
Sun et al. (2023)	SQLi	Author-constructed six datasets (60,000-110,000 | 50,370 / 10,052 - 60,052)	TextCNN + BiLSTM + Attention	Improved detection performance with reduced FP and FN rates	Hybrid TextCNN-BiLSTM architecture
Alghawazi et al. (2023)	SQLi	sql-injection-dataset (Kaggle) (30,907 | 19,529 / 11,378)	RNN Autoencoder	RNN autoencoder outperformed traditional ML models, with 94% accuracy	Deep learning autoencoder-based SQLi detection architecture
Kakisim (2024)	SQLi	Combined GitHub and Kaggle datasets (49,381 | 20,002 / 29,379)	MVC-BiCNN (BiLSTM + CNN)	MVC-BiCNN achieved a detection rate of 99.96%	Multi-View Consensus architecture combining BiLSTM and CNN
Smrity et al. (2025)	SQLi	Three Kaggle datasets (39,074-163,438 | 19,537-81,719 / 19,537-81,719)	SQLGuardNet (Transformer , CNN and LSTM)	Achieved accuracy up to 99.89% across datasets	Multi-branch deep learning architecture with transformer block
Et-tolba et al. (2024)	XSS	Two public HTTP request datasets (13,686-64,833 | 7,373-31,407 / 6,313-33,426)	BiLSTM + Attention + Word2Vec	Achieved 99.56% and 99.11% detection accuracy	Attention-based LSTM model with Word2Vec embeddings
Luu et al. (2025)	XSS	Author-constructed dataset (107,406 | 90,918 / 16,488)	CNN + LSTM	99.27% detection accuracy with low false positive rate	Automatic dataset construction framework for XSS detection
Li et al. (2025)	XSS	XSSed-DMOZ (64,833 | 31,407 / 33,426); Merwani-XSS (42,664 |	CNN + BiLSTM + Attention	Hybrid architecture achieved best accuracy and F1-score	Attention-enhanced CNN-BiLSTM architecture

		27,675 / 14,989)			
Mukamisha et al. (2025a)	SSRF	CIC-URL2016 (15,711 | 7,781 / 7,930)	LSTM, BERT	LSTM achieved 98.2% accuracy	Comparison of LSTM and BERT for SSRF detection
Mukamisha et al. (2025b)	SSRF	CIC-URL2016 (15,711 | 7,781 / 7,930)	LSTM, BiLSTM, GRU, BERT	GRU achieved 99.83% accuracy	Benchmark comparison of deep learning models for SSRF detection

As can be seen in Table 3, many of the reviewed deep learning-based studies combined multiple architectures to improve detection performance. An exception was the RNN autoencoder model used by Alghawazi et al. (2023), which relied on a single architecture. This pattern suggested that combining different deep learning models may improve detection performance, since different models may capture different characteristics of attack payloads. For example, CNN may detect characteristic fragments in malicious SQL queries or injected JavaScript code, while recurrent models such as LSTM or BiLSTM may capture the order of elements within request strings or URLs used in attacks.

Another observation was that, many deep learning-based studies also relied on publicly available datasets, such as those from Kaggle or GitHub, while fewer studies used datasets from cyber security research institutions such as CIC. This observation was consistent with the pattern observed in machine learning-based studies, reflecting similar dataset limitations.

On the other hand, a slight difference was observed in terms of detection performance. Deep learning-based studies often reported very high detection accuracy, frequently above 98% and sometimes exceeding 99%. This range appeared slightly higher than that reported in several machine learning-based studies discussed earlier, although both approaches generally achieved strong results. One possible reason is that deep learning models may capture complex patterns in text-based attack payloads more effectively than machine learning models because they can learn feature representations automatically, rather than relying on manually engineered features such as TF-IDF-based representations.

These observations suggested that recent deep learning-based studies largely followed similar dataset practices to those observed in machine learning-based studies, while distinguishing themselves through the frequent use of hybrid neural architectures and slightly higher reported detection performance.

4.3. Future Studies

Based on the reviewed studies, several future research opportunities may be considered.

First, the research gap in SSRF and other possibly underexplored application-layer attacks could be addressed. By studying less explored attacks such as SSRF and potentially brute-force attacks, future research may contribute to a more comprehensive understanding of application-layer attack detection and support broader cybersecurity awareness by considering a wider variety of attack types and techniques.

Then, the availability of more realistic datasets for cybersecurity research could be improved, since many existing studies relied on publicly available datasets from repositories such as Kaggle or GitHub or on AI-generated datasets.

In addition to these opportunities, future studies may also explore hybrid approaches that combine machine learning and deep learning for application-layer attack detection. Such approaches may improve detection performance by combining feature engineering techniques with the automatic representation learning capabilities of deep learning models.

5. Conclusion

This survey examined recent machine learning and deep learning approaches for detecting three representative application-layer attacks: SQLi, XSS, and SSRF. The reviewed studies were published between 2023 and 2026. By doing so, this chapter provided a structured overview of recent research trends in application-layer attack detection.

The analysis indicated that both machine learning and deep learning approaches achieved high detection performance, although deep learning methods generally reported slightly higher accuracy. It was further indicated that many studies relied on publicly available or synthetic datasets, suggesting limitations in the availability of real-world data for application-layer attack detection.

In addition, relatively fewer studies addressed SSRF detection compared to SQLi and XSS, indicating a potential research gap in the literature on application-layer attack detection. Therefore, future research may benefit from exploring less studied application-layer attacks, developing more realistic cyber security datasets, and investigating hybrid approaches that combine machine learning and deep learning techniques.

Overall, this chapter outlined recent developments in application-layer attack detection and highlighted key research trends and limitations. The findings emphasized the need for more realistic datasets, increased attention to underexplored attacks such as SSRF, and improving the applicability of detection models in real-world environments.

References

OWASP Foundation. (2025). *OWASP Top 10: 2025*. Retrieved from https://owasp.org/Top10/2025/

OWASP Foundation. (2021). *OWASP Top 10: 2021*. Retrieved from https://owasp.org/Top10/2021/

Kumar, S., Dalal, S., & Dixit, V. (2014). The OSI model: Overview of the seven layers of computer networks. *International Journal of Computer Science and Information Technology Research, 2*(3), 461–466.

Borana, G. K., Vishwakarma, N. H., Tamboli, S., Sharma, P., Mukhedkar, M. M., & Dawande, N. A. (2024). Defending the digital world: A comprehensive guide against SQL injection threats. In *Proceedings of the 2024 Second International Conference on Inventive Computing and Informatics (ICICI)* (pp. 707–714). IEEE. https://doi.org/10.1109/ICICI62254.2024.00120

Samo, A., Halepoto, M. A., Awan, K., Jinjhin, J. A., Shaikh, M., & Arain, Q. A. (2024). An in-depth analysis of cross-site scripting (XSS): Threats, mechanisms, and mitigation strategies. In *Proceedings of the 2nd Conference organized by the Benazir Bhutto Shaheed University of Technology and Skill Development* (p. 122). Khairpur Mirs, Pakistan.

Jabiyev, B., Mirzaei, O., Kharraz, A., & Kirda, E. (2021, March). Preventing server-side request forgery attacks. In *Proceedings of the 36th ACM/SIGAPP Symposium on Applied Computing (SAC '21)* (pp. 1626–1635). Association for Computing Machinery. https://doi.org/10.1145/3412841.3442036

Arasteh, B., Karimi, M., Kusetogullari, H., Arasteh, K., & Kiani, F. (2026). A cybersecurity method to detect SQL injection attacks using heuristic-driven feature selection and machine learning algorithms. *The Journal of Supercomputing, 82*, 31. https://doi.org/10.1007/s11227-025-08165-y

Rosca, C. M., Stancu, A., & Popescu, C. (2025). Machine learning models for SQL injection detection. *Electronics, 14*(17), 3420. https://doi.org/10.3390/electronics14173420

Mahmood, S. S. (2025). SQL injection detection using machine learning and explainability. *Journal of Internet Services and Information Security, 15*(2), 309–324.

Qasim, G., Shaikh, T., Ahmed, S., & Tahir, M. (2026). Context-aware and explainable hybrid classification of cross-site scripting attacks using machine learning. *Spectrum of Engineering Sciences, 4*(1), 711–727. https://doi.org/10.5281/zenodo.18387112

Gharai, C., Mohapatra, S. K., Parida, S., Mohanta, R., Chakravarty, S., & Ghosh, D. S. (2025, August). Enhancing web security through machine learning-based feature selection for cross-site scripting (XSS) attacks classification. In

Proceedings of the 2025 IEEE 6th India Council International Subsections Conference (INDISCON) (pp. 1–6). IEEE. https://doi.org/10.1109/INDISCON66021.2025.11251743

Bacha, N., Lu, S., Rehman, A., Idrees, M., Ghadi, Y., & Alahmadi, T. (2024). Deploying hybrid ensemble machine learning techniques for effective cross-site scripting (XSS) attack detection. *Computers, Materials & Continua, 81*(1), 707. https://doi.org/10.32604/cmc.2024.054780

Thaipakdee, T., Promsila, C., Boonyasampan, S., Nimitliupanit, I., & Fugkeaw, S. (2025, February). Scalable machine learning approach for realtime detection of XSS attacks in web applications. In *Proceedings of the 2025 17th International Conference on Knowledge and Smart Technology (KST)* (pp. 17–22). IEEE. https://doi.org/10.1109/KST65016.2025.11003334

Kumthe, L. B. (2024). *SSRF threat detection using AI/ML* (Master's thesis). National College of Ireland.

Quiroz, G. G. C., Voinov, N. V., Drobintsev, P. D., & Zajtsev, I. V. (2025, May). Supervised machine learning for SSRF vulnerability detection. In *Proceedings of the XXVIII International Conference on Soft Computing and Measurements (SCM)* (pp. 206–209). IEEE. https://doi.org/10.1109/SCM66446.2025.11060143

Sun, H., Du, Y., & Li, Q. (2023). Deep learning-based detection technology for SQL injection research and implementation. *Applied Sciences, 13*(16), 9466. https://doi.org/10.3390/app13169466

Alghawazi, M., Alghazzawi, D., & Alarifi, S. (2023). Deep learning architecture for detecting SQL injection attacks based on RNN autoencoder model. *Mathematics, 11*, 3286. https://doi.org/10.3390/math11153286

Kakisim, A. G. (2024). A deep learning approach based on multi-view consensus for SQL injection detection. *International Journal of Information Security, 23*(2), 1541–1556. https://doi.org/10.1007/s10207-023-00791-y

Smrity, T. A., & Muntaqim, M. Z. (2025). SQLGuardNet: Deep learning adaptive processing-based pattern recognition for enhanced SQL injection detection. *Signal, Image and Video Processing, 19*(13), 1152. https://doi.org/10.1007/s11760-025-04642-2

Et-Tolba, M., Hanin, C., & Belmekki, A. (2024, July). DL-based XSS attack detection approach using LSTM neural network with word embeddings. In *Proceedings of the 2024 11th International Conference on Wireless Networks and Mobile Communications (WINCOM)* (pp. 1–6). IEEE. https://doi.org/10.1109/WINCOM62286.2024.10655470

Luu, G. H., Duong, M. K., Pham-Ngo, T. P., Ngo, T. S., Nguyen, D. T., Nguyen, X. H., & Le, K. H. (2024). XSShield: A novel dataset and lightweight hybrid deep learning model for XSS attack detection. *Results in Engineering, 24*, 103363. https://doi.org/10.1016/j.rineng.2024.103363

Li, Z., Liu, F., Gu, Z., & Liu, Y. (2025). XSS attack detection method based on CNN-BiLSTM-attention. *Applied Sciences, 15*, 8924. https://doi.org/10.3390/app15168924

Mukamisha, J., Iradukunda, A., Manzi, E., & Ndibwile, J. D. (2025, October). Benchmarking deep learning models for detecting SSRF vulnerabilities: A comparative study. In *Proceedings of the 2025 IEEE/ACS 22nd International Conference on Computer Systems and Applications (AICCSA)* (pp. 1–7). IEEE. https://doi.org/10.1109/AICCSA66935.2025.11315477

Mukamisha, J., Iradukunda, A., Manzi, E., & Ndibwile, J. D. (2025, April). Mitigating server-side request forgery (SSRF) attacks: An empirical analysis of deep learning-based approaches. In *Proceedings of the 2025 9th International Conference on Cryptography, Security and Privacy (CSP)* (pp. 112–119). IEEE. https://doi.org/10.1109/CSP66295.2025.00027

CHAPTER 3

Evaluation of Munzur Valley National Park as a Sustainable Conservation Area and Conservation Approaches from an Environmental Engineering Perspective

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1. Introduction

Natural protected areas play a crucial role in preserving biodiversity, sustaining ecosystem services, and transferring natural resources to future generations (Zheng et al., 2020). Increasing global population, urbanization, and intensive natural resource use have created significant pressures on natural ecosystems worldwide (Blackie et al., 2025). As a result, the sustainable management of protected natural areas has become a critical research topic within environmental engineering and environmental sciences (Kalabamu, 2026).

Munzur Valley National Park (Figure 1) was declared a national park in 1971 and is one of the largest and most ecologically significant conservation areas in Türkiye. The Munzur River and numerous spring water sources that constitute the hydrological system of the park play a critical role in maintaining the sustainability of aquatic ecosystems in the region. In addition, the national park is notable for hosting hundreds of endemic plant species and a rich diversity of fauna (Sarı & Bidav, 2017).

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Figure 1. Munzur Walley National Park

The Munzur Valley, extending between Tunceli and Ovacık, covers an area of approximately 42,000 hectares and was officially designated as a National Park in 1971. Munzur Valley National Park, one of the largest national parks in Türkiye, begins approximately 8 km from the city center of Tunceli and stretches along the valley to the district of Ovacık. The Munzur Mountains, which rise to elevations of up to 3,300 meters in the northern part of the park, are deeply dissected by the valleys of the Mercan Stream and the Munzur River. In the northern section of the national park, crater lakes located on the high peaks of the Munzur Mountains at elevations between 2,000 and 3,000 meters, springs emerging in the Ovacık plain, canyons, and numerous waterfalls flowing along the valley significantly enhance the natural value and landscape diversity of the park.

Munzur Valley National Park hosts some of the most significant endemic flora and fauna species in Türkiye. With its numerous plant and animal communities, remarkable geomorphological formations, and unique landscape characteristics, the park represents one of the country's most valuable natural heritage regions. The flora of Munzur Valley National Park is particularly rich in biodiversity, with a total of 1,518 plant species recorded. Among these, 43 species are endemic to the Munzur Mountains, while 227 species are endemic to Türkiye. Endemic plants that are found exclusively in the Munzur Mountains include species such as bellflower, Erzincan cherry, Bindebirdelik herb, Munzur buttercup, mountain tea, Munzur Mountain oltu herb, and various violet species.

Approximately 1.5 km downstream from the Munzur springs, birch stands—one of the characteristic tree species of the region—are located along both sides of the Munzur River. Birch, which is considered a relatively rare tree species in Türkiye, develops well-formed trunks along riverbanks in this region and contributes significantly to the botanical richness of the area. The dominant tree species within the national park is oak, and non-rocky slopes and hill areas are largely covered by oak forests. In the valley floor and along riverbanks, a highly diverse vegetation structure exists, consisting of elm, maple, alder, ash, plane tree, vine, birch, walnut, wild hazelnut, poplar, willow, and various shrub species, forming a rich and heterogeneous plant community.

The natural environment of Munzur Valley National Park provides highly suitable habitats for a wide variety of wildlife species. The park hosts several remarkable and rare species that are characteristic of the region, including the wild goat species known as the bezoar goat (Figure 3) and the wild mountain goat (Figure 2), as well as game birds such as the chukar partridge (Figure 4).

In addition to these species, the national park supports a diverse range of mammals, including wolves, foxes, martens, bears, lynxes, otters, badgers, squirrels, hares, wild boars, and wild goats. The brown bear (Figure 5), which inhabits caves and rocky cavities, is one of the most significant large mammals within the Munzur wildlife ecosystem. Other prominent large mammals in the region include the lynx (Figure 6), which typically inhabits rocky areas within forested landscapes, as well as the wild boar (Figure 7) and the wolf (Figure 8).

Munzur Valley National Park is also particularly rich in terms of avian diversity. Among the birds of prey present in the park are species such as eagles, vultures, falcons, hawks, sparrowhawks, kestrels, harriers, and kites. One of the rare and notable species observed in the region is the golden eagle (Figure 9). Nocturnal predators such as the eagle owl, various owl species, and bats are also commonly found in the park.

The national park hosts a wide range of other bird species, including partridges, grey partridges, great bustards, cranes, quails, woodcocks, turtle doves, wood pigeons, rock pigeons, several duck species, and occasionally geese. In addition, the Munzur River, Mercan Stream (Figure 10), and surrounding water systems support abundant populations of trout, which constitute an important economic resource for the local community.

Figure 2. Hook-horned goat.

Figure 3. Benzuvar.


Figure 4. Urial partridge.


Figure 5. Brown bear.


Figure 6. Lynx


Figure 7. Tunceli Wild Boar


Figure 8. Tunceli Wolf


Figure 9. Tunceli Golden Eagle

Şekil 10. Mercan river

However, increasing tourism activities, settlement pressures, and the intensive use of natural resources pose various environmental risks to the ecosystems of the national park. These pressures may lead to habitat degradation, pollution, and ecological imbalance if not properly managed. Therefore, it is essential to evaluate the national park as a sustainable conservation area and to develop scientifically based environmental management strategies aimed at ensuring the long-term protection and sustainability of its natural ecosystems.

2. Research Gap

A significant portion of the existing studies on Munzur Valley National Park primarily focus on the region's biodiversity, particularly its flora and fauna characteristics. However, studies that evaluate the sustainable environmental management of the national park from an environmental engineering perspective remain relatively limited in the literature.

In particular, integrated management models that simultaneously address water resource management, wastewater and solid waste control, environmental monitoring systems, and sustainable tourism planning have not been sufficiently examined. Therefore, this study aims to fill this research gap by proposing a comprehensive environmental engineering-based approach for the sustainable management of Munzur Valley National Park.

3. Scientific Contribution

This study makes three main contributions to the literature:

Evaluation of natural conservation areas from an environmental engineering perspective

The study comprehensively addresses the technical and environmental management tools for the sustainable management of Munzur Valley National Park.

Proposal of an integrated environmental management model

The research presents a conceptual model that evaluates water quality monitoring, wastewater management, habitat protection, and sustainable tourism approaches together.

Provision of policy and implementation recommendations

The study proposes feasible environmental management strategies for the sustainable management of natural conservation areas.

4. Method

4. 1. Research Framework

In this model, environmental management tools protect the components of the ecological system, while sustainable use factors ensure the long-term continuity of this process. This study is based on a qualitative research approach. The research examined academic studies on sustainable national park management, river ecosystems, and environmental management. The integrated sustainable management model proposed for Munzur Valley Natural Park is presented in Figure 11.

Figure 11. Integrated Sustaşinable Management Model for Munzur Valley National Park

The following environmental engineering tools were evaluated as part of the research:

4.1.1 Water quality monitoring systems

Protecting water quality in the Munzur basin is critically important for the sustainability of the ecosystem. Therefore, continuous and scientifically based water quality monitoring systems should be established.

Automatic sensor systems: Sensors placed at specific points along the river can continuously measure the following parameters:

-pH

-dissolved oxygen

-temperature

-electrical conductivity

-turbidity

-nitrate and phosphate levels

Remote monitoring (IoT-based systems): Data obtained from the sensors are transferred to cloud-based platforms and real-time monitoring is performed.

Early warning system: When pollution levels exceed threshold values, an automatic alarm system is activated.

Periodic laboratory analyses: Parameters such as heavy metals, pesticides, and microplastics should be analyzed regularly. Thanks to these systems, a long-term hydrological and ecological database can be created for the Munzur Rive

4.1.2. Wastewater and Waste mannagement systems

Settlements and tourism activities surrounding the national park have the potential to cause water and soil pollution.

Wastewater management:

• Natural treatment systems (constructed wetlands)

• Biological treatment plants

• Package treatment systems in settlements

• Zero discharge policy for tourist facilities

Solid waste management:

• Source separation system

• Recycling centers

• Composting systems for organic waste

• Smart bins in tourist areas

Policy recommendations:

• Restriction of single-use plastics within park boundaries

• "Leave No Trace" tourism policy

4.1.3. Ecossytem based protection

Ecosystem-based conservation approach aims to protect the entire ecological system, not just specific species. Key components:

• Habitat protection

• Monitoring of endemic plant and animal species

• Protection of ecological corridors

• Protection of the natural flow of the water regime

Since the Munzur Valley is a particularly rich area in terms of endemic plants and wildlife, conservation policies should be planned in a way that protects habitat integrity.

Proposed practices:

• Creation of a biodiversity database

• Habitat monitoring with drone and remote sensing technologies

• Ecological restoration projects

4.1.4. Basin-Based Planning

The sustainable management of the Munzur River should be planned not only within the park boundaries but also on the scale of the entire Munzur basin.

Basin management model:

• Hydrological analysis

• Land use planning

• Identification of pollutant sources

• Water allocation and ecological flow management

Integrated basin management:

• Local governments

• Academics

• Civil society organizations

• Local people

4.2. Sustainable Tourism Management

Munzur Valley has great potential in terms of nature tourism. However, uncontrolled tourism can put pressure on the ecosystem.

4.2.1. Sustainable tourism strategies

• Determining Visitor Carrying Capacity

• Creating Ecotourism Routes

• Guided Nature Walks

• Environmental Education Programs

4.2.2. Green tourism applications

• Transportation Systems that Reduce Carbon Footprint

• Environmentally Friendly Accommodation Facilities

• Participation of Local People in Tourism Revenue

5. Results and dissussiom

5.1 Protection of Water Resources

The streams and spring waters within the national park are critically important for the ecosystem balance. In particular, the Munzur River forms the basis of the park's hydrological system. Therefore, continuous monitoring of water quality and control of potential pollution sources are necessary (Kocaman and Celik, 2025).

5.2 Waste Management

Tourism activities and residential areas can increase solid waste generation. Therefore, effective implementation of waste management systems is necessary (Cornejo et al., 2026).

5.3 Habitat Protection

The protection of riparyan vegetation (Figure 12) and habitat restoration are important for the sustainability of national park ecosystems.

Figure 12. Dominant vegetation in Tunceli.

This study demonstrates that environmental engineering-based approaches play a critical role in the sustainable management of Munzur Valley National Park. One of the main problems encountered in many natural conservation areas in the literature is that conservation policies are only focused on biodiversity and technical environmental management tools are not used sufficiently (Ahamad et al., 2024). In this context, the integration of engineering-based environmental monitoring systems is necessary in the sustainable management of national parks.

The establishment of continuous monitoring systems in terms of water resource conservation can enable early pollution detection, especially in mountainous and sensitive ecosystems (Zang, 2025). Thanks to advanced sensor technologies and automated measurement systems, water quality parameters can be monitored in real time. This approach will contribute to reducing negative impacts on the ecosystem by enabling the rapid detection of potential pollution sources (Wang et al., 2024).

Furthermore, sustainable tourism management stands out as an important element in the conservation of national parks (Danzi et al., 2025). Ecotourism activities offer significant opportunities for regional development, but when carried out uncontrollably, they can put pressure on the ecosystem (Lukoseviciute et al., 2024). Therefore, it is necessary to determine visitor capacity and conduct environmental impact assessments.

Finally, the involvement of the local community in conservation processes enhances the success of sustainable environmental management (Haile and Singh, 2026). Active participation of the local population in environmental conservation activities increases awareness of the conservation of natural resources. This will contribute to the development of a participatory and sustainable model in national park management.

Munzur Valley National Park, with its biodiversity, water resources, and natural ecosystem structure, is one of Turkey's most important sustainable conservation areas. For the long-term conservation of the national park:

• water quality monitoring systems should be established

• wastewater and solid waste management should be strengthened

• habitat conservation efforts should be carried out

• sustainable tourism policies should be implemented

The implementation of these strategies will significantly contribute to the conservation of the national park ecosystem and the sustainable management of natural resources.

REFERENCES

Ahamad, S., Abdulla, M., Saquib, M., Hussain, M.K. (2024). Pseudo-Natural Products: Expanding chemical and biological space by surpassing natural constraints, Bioorganic Chemistry, 150, 107525.

Blackie, I.R., Maphosa, F., Garekae, H., Nkhukhu-Orlando, E. (2025). Land rights, natural resources management, climate change and ethno-politics in postcolonial Botswana, Land Use Policy, 159, 107811.

Cornejo, D., Martí, E., Margenat, H., Serra-Rada, J., Martínez, M., Guasch, H.. (2026). Tourism, waste management and macroplastic accumulation in headwater riparian-stream ecosystems, Environmental Advances. 23, 100691.

Danzi L., Orchiston, C., Higham, J. (2025). Effectiveness and sustainability of collaborative networks in tourism disaster management, International Journal of Disaster Risk Reduction, 129, 105775.

Guo, Q., Guo, F. How does natural resource asset departure audit affect corporate green innovation? Based on enhancement of environmental awareness, International Review of Economics & Finance, 106, 104998.

Haile, M.B., Singh, S. (2026). The link between green management practices and sustainable environmental performance through the mediating role of employee green behavior: Evidence from large-scale manufacturing organizations, Acta Psychologica, 263, 106275.

Kalabamu, F.T. (2019). Land tenure reforms and persistence of land conflicts in Sub-Saharan Africa. The case of Botswana, Land Use Policy, 81, 337-345

Kocaman, M.S., Celik, R. (2025). Diyarbakır Organize Sanayi Bölgesi Yeraltı Sularının Kirlilik Riskinin Araştırılması. Dicle Üniversitesi Fen Bilimleri Enstitüsü Dergisi 14 (1), 27-43

Lukoseviciute, G., Henriques, C.N., Pereira, L.N., Panagopoulos, T. (2024). Participatory development and management of eco-cultural trails in sustainable tourism destinations, Journal of Outdoor Recreation and Tourism, 47, 100779.

Sarı, C., Bidav, Y. (2017). Munzur Vadisi Milli Parkı'nda Doğal ve Kültürel Çevrenin Geliştirilmesi ve Korunması Üzerine Yöre Halkının Farkındalığı. Doğu Coğrafya Dergisi, 22(38), 63-86.

Wang, Q., Liu, S., Wang, G.A Y., Xue, B., Xu, Z., Wu, J. (2024). Development of ecological environment monitoring network system in China. Strategic Study of CAE. 26(5), 212–222.

Zhang, D. (2025). Establishing a nation-wide eco-environment monitoring network for sustainable governance. Environ Sci Ecotechnol. 30 (26), 100585.

Zheng, H., Klein, N., Wang, L., Kay, S., Herzog, F., Shi, R., Liu, R., Bogaert, J. (2026). Semi-natural habitats enhance bird diversity in intensively managed farmlands in North China, Ecological Indicators, 183, 114666

CHAPTER 4

A Compromise-Based Techno-Economic Assessment of Grid-Connected Green Hydrogen Production Systems

Batın Demircan[1] & Metin Gül[2]

1. Introduction

Hydrogen has emerged as a key energy carrier in the transition toward low-carbon and sustainable energy systems, owing to its versatility, high gravimetric energy density, and potential to decarbonize sectors that are difficult to electrify directly. In particular, green hydrogen produced via water electrolysis using renewable electricity is widely recognized as a critical component of future energy systems, enabling large-scale integration of variable renewable energy sources while significantly reducing greenhouse gas emissions (Buttler & Spliethoff, 2018; Glenk & Reichelstein, 2019).

Recent studies emphasize that the role of hydrogen extends beyond energy storage, acting as a coupling vector between the power, transport, and industrial sectors (Egeland-Eriksen, Hajizadeh, & Sartori, 2021; Staffell et al., 2019). However, despite its strategic relevance, the widespread deployment of green hydrogen remains constrained by economic challenges. High capital costs associated with renewable power generation and electrolyzer technologies, combined with fluctuating electricity prices and resource variability, continue to limit cost competitiveness compared to conventional hydrogen production pathways (Bhandari & Adhikari, 2024; Franzmann, Schmid, & Sterner, 2023; Glenk & Reichelstein, 2019). These challenges highlight the need for systematic evaluation of hydrogen production system designs that balance economic feasibility with environmental performance.

Grid-connected renewable hydrogen production systems have gained increasing attention as a pragmatic approach to mitigate renewable intermittency while maintaining stable electrolyzer operation. By allowing electricity exchange with the grid, such systems can ensure continuous hydrogen production without excessive oversizing of renewable capacities (Dufo-L'opez & Bernal-Agust'in, 2008; Egeland-Eriksen et al., 2021). Nevertheless, grid interaction introduces

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additional trade-offs, as increased grid electricity use may raise emissions and operating costs, whereas excessive renewable deployment can lead to higher capital investment and inefficient surplus energy export (Franzmann et al., 2023; Glenk & Reichelstein, 2019). Capturing these competing effects requires comprehensive techno-economic analysis at the system level.

Simulation-based tools such as HOMER have been widely employed to analyze hybrid renewable energy systems and hydrogen-based configurations under realistic operating conditions. HOMER enables time-resolved modeling of energy balances, system costs, and component interactions, providing a consistent framework for evaluating alternative system designs (Dufo-L'opez & Bernal-Agust'in, 2008; Lambert, 2005). However, while simulation tools are effective in generating feasible solutions, they are not inherently designed to support decision-making when multiple conflicting performance criteria must be considered simultaneously (Dufo-L'opez & Bernal-Agust'in, 2008; Pohekar & Ramachandran, 2004).

To address this limitation, multi-criteria decision-making (MCDM) approaches have been increasingly applied in the context of sustainable energy planning. Comprehensive reviews have demonstrated that MCDM methods are particularly suitable for evaluating complex energy systems involving economic, environmental, and technical trade-offs (Dufo-L'opez & Bernal-Agust'in, 2008; Pohekar & Ramachandran, 2004). Among these methods, compromise-based techniques such as VIKOR are especially effective when decision-makers seek balanced solutions rather than extreme optima driven by a single criterion(S Opricovic & Tzeng, 2004). The VIKOR method explicitly considers both overall system performance and the maximum individual regret associated with specific criteria, making it well suited for renewable hydrogen system design problems.

Several recent studies have successfully combined techno-economic modeling with MCDM techniques to evaluate hydrogen and hybrid renewable systems, demonstrating the value of integrated decision-support frameworks (Dufo-L'opez & Bernal-Agust'in, 2008; Egeland-Eriksen et al., 2021; Franzmann et al., 2023). Nevertheless, many existing works either focus on off-grid configurations or emphasize single-objective optimization, limiting their applicability to real-world, grid-connected hydrogen production scenarios operating under continuous load conditions.

In this context, the present study proposes an integrated framework that combines HOMER-based techno-economic simulation with VIKOR-based multi-criteria decision analysis to evaluate grid-connected green hydrogen production systems. A 1 MW electrolyzer operating continuously is considered as the core hydrogen production unit, while photovoltaic and wind power capacities are systematically varied to generate feasible system alternatives. A comprehensive set of economic, environmental, and grid interaction indicators is extracted and structured into a decision matrix, enabling compromise-based ranking of system configurations.

The main contribution of this study lies in providing a transparent and transferable decision-support framework that captures the inherent trade-offs between hydrogen production cost, renewable integration, grid dependency, and environmental impact. By clearly separating physical system simulation from multi-criteria evaluation, the proposed approach avoids black-box optimization and enhances interpretability, offering practical insights for researchers, system designers, and policymakers involved in large-scale green hydrogen deployment..

2. Materials and Method

In this chapter, an integrated methodological framework is proposed to evaluate alternative renewable-based hydrogen production system designs by combining detailed techno-economic simulation with multi-criteria decision-making. The motivation behind this approach is the recognition that the performance of green hydrogen systems cannot be assessed through a single indicator alone. Instead, economic feasibility, renewable energy penetration, environmental performance, and interaction with the electricity grid must be considered simultaneously in a structured and transparent manner.

2.1 Overall Methodological Framework

In this chapter, an integrated methodological framework is proposed to evaluate alternative renewable-based hydrogen production system designs by combining detailed techno-economic simulation with multi-criteria decision-making. The motivation behind this approach is the recognition that the performance of green hydrogen systems cannot be assessed through a single indicator alone. Instead, economic feasibility, renewable energy penetration, environmental performance, and interaction with the electricity grid must be considered simultaneously in a structured and transparent manner.

The methodology follows a two-stage structure. In the first stage, the physical and economic behavior of the hydrogen production system is modeled using the HOMER software platform. HOMER is employed to simulate a grid-connected hybrid renewable energy system consisting of photovoltaic and wind power generation units supplying a continuously operating 1 MW electrolyzer. By systematically varying the installed capacities of photovoltaic and wind power while allowing grid electricity exchange, a wide range of technically feasible system configurations is generated. For each configuration, HOMER calculates key performance indicators such as net present cost, operating costs, renewable fraction, grid electricity purchases and sales, and annual CO_2 emissions.

In the second stage, the set of feasible system configurations obtained from HOMER is evaluated using the VIKOR method, which is a compromise-based multi-criteria decision-making technique. Rather than identifying an extreme optimum based on a single objective, VIKOR focuses on selecting solutions that achieve a reasonable balance among conflicting criteria. This is particularly relevant for hydrogen production systems, where cost minimization, emission reduction, and increased renewable penetration often lead to opposing design choices. By considering both the overall deviation from ideal performance and the worst-case criterion deviation, the VIKOR method enables the identification of balanced and practically meaningful solutions.

A key feature of the proposed framework is the clear separation between system simulation and decision analysis. HOMER is exclusively used to generate consistent and reproducible techno-economic data based on physical system behavior, while the multi-criteria evaluation is carried out as a post-processing step using an external decision-making method. This separation improves methodological transparency and allows the influence of individual criteria and assumptions to be clearly traced throughout the analysis.

The complete methodological workflow—from system definition and scenario generation to multi-criteria evaluation and final ranking of alternatives—is summarized schematically in Figure 1.By structuring the analysis in this manner, the proposed framework provides a flexible and transferable decision-support tool that can be applied to different locations, system scales, and renewable resource conditions without loss of generality.

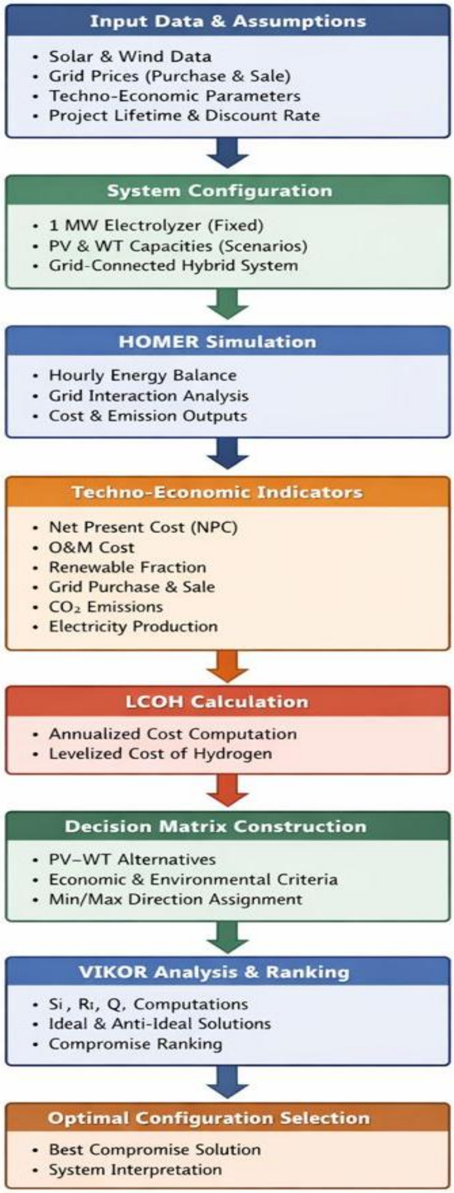

Figure 2 Flowchart of The Methodology

2.2 System Configuration and Scenario Definition

The hydrogen production system considered in this study (Figure 2) is designed as a grid-connected hybrid renewable energy system to ensure continuous operation of a large-scale electrolyzer. A 1 MW water electrolyzer is selected as the core production unit and is assumed to operate continuously throughout the year, representing an industrially relevant hydrogen production facility. This assumption allows the analysis to focus on system-level design trade-offs rather than short-term operational fluctuations.

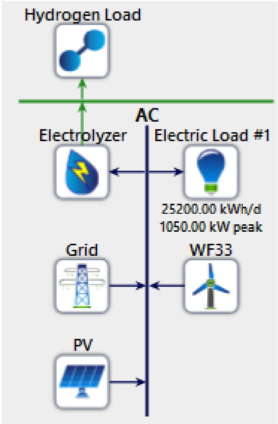

Figure 2 System Configuration

Electricity for the electrolyzer is supplied by photovoltaic (PV) and wind power generation, with the electricity grid providing additional power when renewable generation is insufficient. When renewable electricity exceeds the electrolyzer demand, surplus power is exported to the grid. This bidirectional grid interaction reflects realistic operating conditions and introduces flexibility in managing renewable variability while maintaining uninterrupted hydrogen production. Photovoltaic and wind capacities are treated as design variables and systematically varied to generate alternative system configurations. In contrast, the electrolyzer capacity is fixed at 1 MW for all scenarios, ensuring a consistent basis for comparison. Grid connection is assumed to be available in all cases, with no restrictions on electricity import, allowing full-load electrolyzer operation under all conditions.

System operation follows a load-following dispatch strategy, where renewable electricity is prioritized for hydrogen production and the grid supplies any remaining demand. This operational approach naturally creates trade-offs between renewable penetration, grid dependency, and system cost. Each scenario is therefore defined by a unique PV–wind capacity combination and its associated techno-economic and environmental performance indicators, which form the basis for the subsequent multi-criteria decision-making analysis.

2.3. HOMER-Based Techno-Economic Modeling and LCOH Assessment

The techno-economic performance of the proposed hydrogen production system is evaluated using the HOMER software environment, which enables time-resolved simulation of hybrid renewable energy systems under realistic operational and economic constraints. HOMER is employed to simulate the annual operation of each system configuration and to compute the associated cost and energy balance components that form the basis of the economic assessment. The key parameters of the system configuration is given in Table 1.

Table 2 Key Techno-Economic Parameters

Parameter	**Value**
Scaled Average Load	25200 kWh/d
Timestep	60 mins
Location	Aydın/Türkiye ($37^0$22.6'N,$27^0$15,9'E)
Lifetime	20 Years
Capex Electrolyzer	1444444 $/MW
Opex Electrolyzer	43000 $/MW
Capex PV	1247000 $/MW
Opex PV	20400 $/MW
Capex Wind	701000 $/0.5MW
Opex Wind	14420 $/0.5MW
Grid Price	0.1 $/kW
Grid Sellback Price	0.07 $/kW

For each scenario defined by a specific combination of photovoltaic and wind power capacities, HOMER calculates the total net present cost (NPC) of the system by accounting for capital expenditures, component replacements, operation and maintenance costs, and electricity transactions with the grid over the project lifetime. These cost components are aggregated using a discounted cash flow approach, ensuring that long-term economic performance is consistently represented across all alternatives. Although HOMER internally accounts for the costs associated with electrolyzer operation, it does not directly report the levelized cost of hydrogen (LCOH) as a standalone output for grid-connected systems. Therefore, in this study, LCOH is calculated as a post-processing metric based on HOMER's techno-economic results. This approach allows hydrogen production cost to be explicitly linked to system-wide economic performance rather than treated as an isolated component-level indicator.

The LCOH is defined as the ratio of the annualized total system cost to the annual hydrogen production, expressed as (Steward, Ramsden, & Zuboy, 2009):

$$\text{LCOH} = \frac{C_{\text{ann}}}{m_{\text{H}_2,\text{ann}}} \quad (1)$$

where C_{ann}represents the annualized system cost derived from the net present cost using the capital recovery factor, and $m_{\text{H}_2,\text{ann}}$denotes the annual hydrogen production. The annualized cost is obtained as:

$$C_{\text{ann}} = \text{NPC} \times \frac{i(1+i)^N}{(1+i)^N - 1} \quad (2)$$

where i is the real discount rate and N is the project lifetime. Annual hydrogen production is determined from the electricity consumed by the electrolyzer and its specific energy consumption, assuming continuous operation of the 1 MW unit.

By calculating LCOH in this manner, the hydrogen production cost inherently reflects the combined effects of renewable energy penetration, grid electricity usage, system oversizing, and operational flexibility. As a result, LCOH serves as a comprehensive economic indicator that directly captures the trade-offs between investment cost, operating expenses, and renewable resource utilization. The resulting LCOH values, together with other techno-economic and environmental indicators obtained from HOMER, are used as decision criteria in the subsequent multi-criteria decision-making analysis. This ensures that hydrogen production cost is explicitly considered alongside complementary performance metrics such as net present cost, renewable fraction, grid dependency, and carbon emissions.

2.4. Decision Criteria Selection and Classification

The selection of decision criteria is a critical step in evaluating renewable-based hydrogen production systems, as system performance cannot be captured by a single economic or technical indicator. In this study, the criteria are chosen to reflect the multi-dimensional nature of green hydrogen systems, where economic performance, environmental impact, renewable energy utilization, and grid interaction must be assessed together. All criteria are directly derived from techno-economic simulation outputs, ensuring consistency, transparency, and reproducibility.

Economic performance is represented by NPC, operating cost, initial capital cost, operation and maintenance cost, and the LCOH. While NPC reflects long-term system cost, LCOH is emphasized as the key indicator of hydrogen cost competitiveness. Environmental performance is evaluated using renewable fraction and annual CO_2 emissions, capturing the trade-off between renewable integration and indirect emissions from grid electricity use.

System interaction with the electricity grid is explicitly included through grid electricity purchased and grid electricity sold, representing grid dependency and surplus renewable generation, respectively. For clarity, all criteria are grouped into economic, environmental, and grid interaction categories, with each criterion assigned a clear optimization direction. This structured and balanced selection ensures that the final ranking reflects not only cost efficiency, but also practical feasibility and environmental relevance.

2.5. Construction of the Decision Matrix

Following the techno-economic simulations, all feasible system configurations are organized into a structured decision matrix for multi-criteria evaluation. Each alternative represents a unique combination of photovoltaic and wind capacities that ensures continuous operation of the 1 MW electrolyzer. While PV and wind sizes define the alternatives, they are treated as design descriptors rather than decision criteria.

The decision matrix is constructed using performance indicators directly obtained from simulation outputs and post-processed results, covering economic, environmental, and grid interaction aspects. Cost-related indicators, including net present cost, operating cost, capital cost, operation and maintenance cost, and LCOH, are defined as minimization criteria. Renewable fraction and annual electricity production are treated as maximization criteria, while grid electricity purchased and CO_2 emissions are minimized to reflect reduced grid dependency and environmental impact. Grid electricity sold is included as an indicator of surplus renewable generation and system flexibility.

All indicators are assembled into a transparent decision matrix without prior weighting or normalization. This ensures a clear and traceable link between system simulation and decision analysis, with normalization and compromise ranking carried out within the VIKOR framework. The adopted structure allows the influence of each criterion on the final ranking to be explicitly examined and supports reproducibility of the methodology..

2.6. VIKOR Methodology and Compromise Ranking

To evaluate and rank the alternative hydrogen production system configurations, the VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje) method is adopted as the multi-criteria decision-making technique (Serafim Opricovic & Tzeng, 2007). VIKOR is particularly suitable for complex energy system design problems in which multiple conflicting criteria must be considered simultaneously and where a compromise solution is preferred over an extreme optimum driven by a single performance indicator.

The VIKOR procedure begins with the construction of a normalized decision matrix based on the raw performance values obtained from the HOMER simulations. For each criterion j, the best (ideal) value $f_j^*$and the worst (anti-ideal) value $f_j^-$are identified according to the predefined optimization direction:

- For benefit-type (maximization) criteria:

$$f_j^* = \max_i f_{ij}, f_j^- = \min_i f_{ij} \quad (3)$$

- For cost-type (minimization) criteria:

$$f_j^* = \min_i f_{ij}, f_j^- = \max_i f_{ij} \quad (4)$$

Using these reference values, the normalized distance of each alternative $i$from the ideal solution for criterion $j$is calculated as:

$$d_{ij} = \frac{f_j^* - f_{ij}}{f_j^* - f_j^-} \quad (5)$$

This normalization ensures that all criteria are expressed on a dimensionless and comparable scale, where lower values indicate closer proximity to the ideal performance. Based on the normalized distances, two aggregate performance measures are computed for each alternative. The first is the group utility measure S_i, which represents the weighted sum of deviations across all criteria:

$$S_i = \sum_{j=1}^{m} w_j \, d_{ij} \quad (6)$$

where $w_j$denotes the weight of criterion j, and $m$is the total number of criteria.

The second measure is the individual regret measure R_i, which captures the maximum deviation from the ideal solution among all criteria:

$$R_i = \max_j \left(w_j \, d_{ij}\right) \quad (7)$$

While $S_i$reflects the overall performance of an alternative considering all criteria simultaneously, $R_i$highlights the weakest-performing criterion and prevents solutions with severe deficiencies in any single aspect from being overlooked.

The final VIKOR index $Q_i$is then calculated as a compromise between group utility and individual regret:

$$Q_i = v \frac{S_i - S^*}{S^- - S^*} + (1 - v) \frac{R_i - R^*}{R^- - R^*} \quad (8)$$

where:

- $S^* = \min_i S_i, \quad S^- = \max_i S_i$
- $R^* = \min_i R_i, \quad R^- = \max_i R_i$

- $v \in [0,1]$ is the compromise parameter representing the decision strategy.

In this study, the value $v = 0.5$ is selected to represent an equal emphasis on overall system performance and avoidance of extreme individual regret. This balanced strategy is particularly appropriate for green hydrogen systems, where economic efficiency, renewable integration, and grid dependency must be considered with comparable importance. Alternatives are ranked in ascending order of the $Q_i$index, with lower values indicating solutions closer to the ideal compromise. The rankings obtained from S_i, R_i, and $Q_i$are jointly examined to interpret whether the preferred solutions are driven by strong overall performance, low individual regret, or a balanced combination of both.

By incorporating this full set of VIKOR formulations, the methodology provides a transparent and mathematically rigorous framework for compromise-based decision-making. This approach allows the identification of hydrogen production system designs that are not only cost-effective, but also balanced in terms of renewable utilization, environmental performance, and grid interaction characteristics.

3. Results

This section presents the results of the integrated techno-economic simulation and multi-criteria evaluation. First, key economic, environmental, and operational indicators of the grid-connected hydrogen production system are examined based on simulation outputs. Then, the VIKOR method is used to rank the feasible alternatives and identify a compromise solution that balances cost, renewable integration, and grid interaction. The findings are discussed using graphical analyses to highlight trade-offs, clustering behavior, and dominant design patterns within the solution space.

3.1. VIKOR-Based Compromise Ranking Results

The VIKOR analysis reveals a clear clustering of most feasible system configurations within a narrow performance range (S ≈ 0.45–0.60, Q ≈ 0.10–0.11), indicating limited differentiation among many alternatives. In contrast, the best-performing alternative (A1, RowID = 154) is distinctly separated from this cluster, with S ≈ 0.39 and Q ≈ 0.064, corresponding to the lowest compromise index (P ≈ 0.07). This outcome reflects a well-balanced trade-off between overall system performance and individual criterion regret, supporting its selection as the compromise-optimal solution.

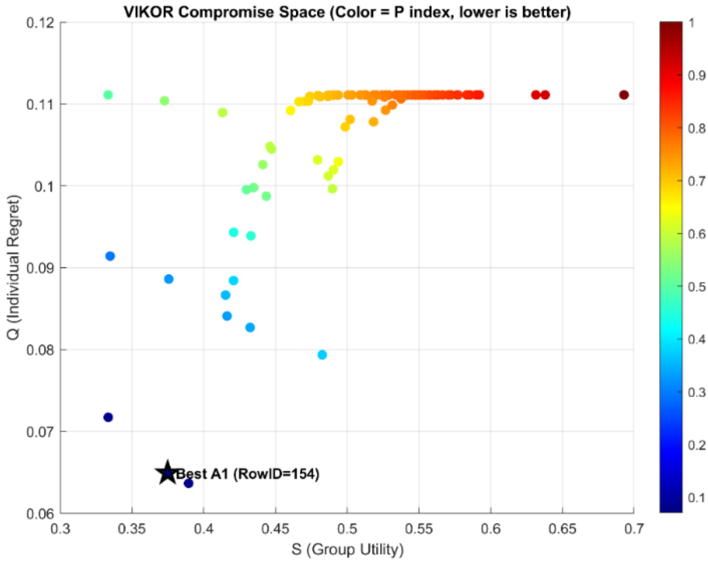

Figure 3 VIKOR compromise space (S–Q) for all feasible system alternatives.

3.2. Ranking of Top Alternatives

Figure 4 shows the top 15 alternatives ranked by the VIKOR compromise index (P). A clear separation is observed between the first four alternatives and the rest of the solution set. While the best-performing configurations achieve P values below 0.10—led by the top-ranked case (ID = 154) with P ≈ 0.07—the remaining alternatives rapidly shift to higher P values in the range of 0.30–0.46. This pattern indicates that only a limited number of configurations are able to jointly satisfy economic, technical, and environmental criteria at a comparable level.

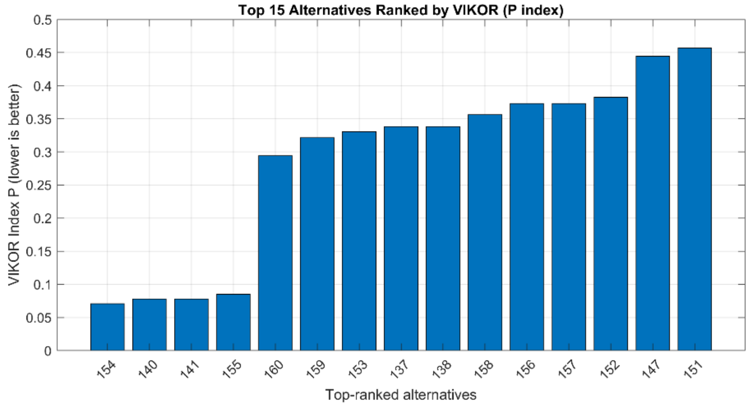

Figure 4 Top 15 alternatives ranked by the VIKOR compromise index (P).

3.3. Criterion-Level Regret Analysis

Figure 5 presents the normalized regret matrix for the top-ranked alternatives. The results show that economic criteria—particularly NPC and operating cost—are the main sources of regret across most configurations. In contrast, renewable fraction and CO_2 emissions display relatively low and stable regret values among the best-performing solutions, indicating that environmental performance is not the primary limiting factor within the feasible design space. The top-ranked alternative maintains consistently low regret across all criteria, whereas lower-ranked cases exhibit pronounced regret in grid electricity purchased and LCOH, leading to weaker overall compromise performance.

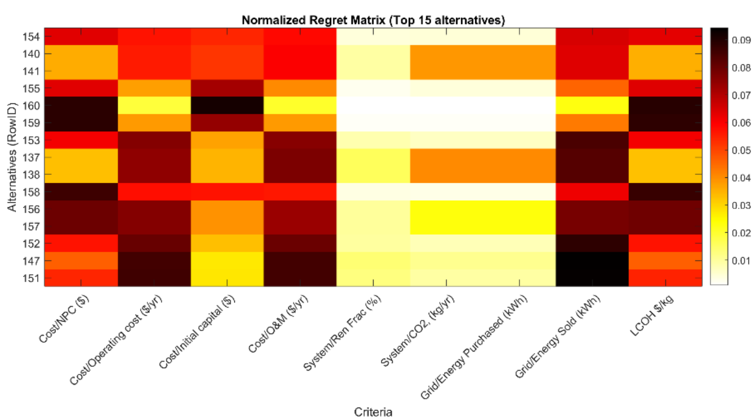

Figure 5 Normalized regret matrix of the top 15 VIKOR-ranked alternatives.

3.4. Design Space Interpretation: PV and Wind Capacities

The distribution of alternatives is presented in Figure 6. The best-ranked configuration corresponds to a moderate PV capacity (≈ 15–17 MW) combined with a wind capacity of approximately 8–9 MW. This outcome highlights that oversizing renewable components does not necessarily improve overall system optimality when grid interaction and economic constraints are considered.

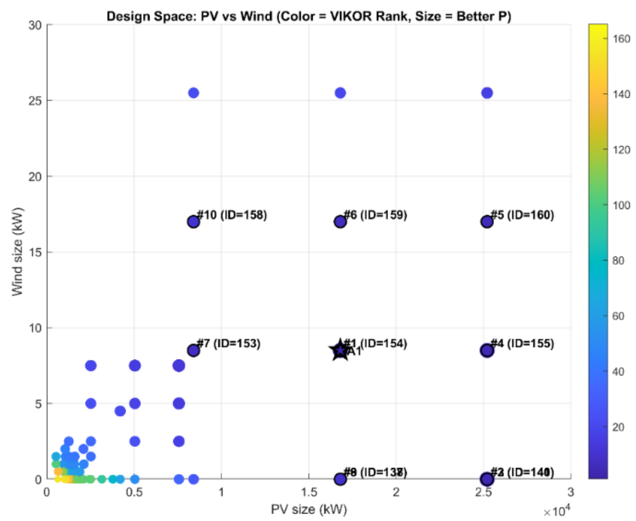

Figure 6 PV–wind design space colored by VIKOR ranking.

4.5. Trade-Off Between Renewable Fraction and Hydrogen Cost

Figure 7 illustrates the trade-off between renewable fraction and LCOH. The results show a clear nonlinear relationship between these two indicators. For renewable fractions up to approximately 40–45%, LCOH remains relatively stable at 4.9–5.1 $/kg. Beyond this range, LCOH increases rapidly, exceeding 6.5 $/kg for renewable fractions above 85–90%. The compromise-optimal solution achieves a renewable fraction of approximately 90–92% with an associated LCOH of about 6.6 $/kg, representing a balanced solution that avoids the steep cost escalation observed in near fully renewable configurations.

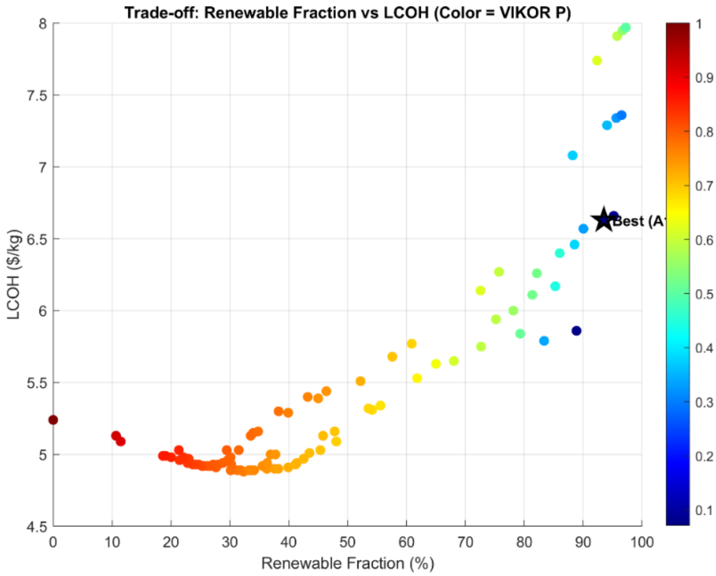

Figure 7 Trade-off between renewable fraction and LCOH colored by VIKOR index.

Overall, the results demonstrate that compromise-based multi-criteria evaluation provides insights that cannot be obtained from single-objective optimization alone. While high renewable penetration reduces grid dependency and emissions, it simultaneously increases system costs and excess electricity generation. The selected compromise solution effectively balances these competing objectives, offering a techno-economically viable and environmentally robust configuration for grid-connected green hydrogen production. These findings underline the importance of integrated decision-support frameworks in hydrogen system planning, particularly in contexts where grid interaction, investment constraints, and sustainability targets must be addressed simultaneously.

4. Conclusion

This study developed an integrated framework to evaluate grid-connected green hydrogen production systems by combining detailed techno-economic simulation with compromise-based MCDM analysis. A 1 MW electrolyzer was taken as the reference hydrogen production unit with an on-grid PV and wind capacities. The results show that system designs optimized using a single performance indicator, such as minimum cost or maximum renewable fraction, often lead to impractical outcomes. While high renewable penetration reduces grid dependency and emissions, it also causes a rapid increase in capital investment and hydrogen production cost. Conversely, configurations with lower renewable shares achieve lower LCOH values but rely more heavily on grid electricity, increasing both emissions and operational risk. By applying the VIKOR method, these objectives were evaluated simultaneously. Only a limited number of alternatives were found to provide a balanced performance across economic, environmental, and grid-related criteria. The compromise-optimal solution is characterized by moderate PV and wind capacities with a renewable fraction of around 90–92% with an LCOH of 6.6 $/kg. This configuration is located near the knee point of the renewable fraction–LCOH trade-off curve, where additional renewable integration would lead to disproportionate cost increases. The regret analysis further indicates that economic indicators—particularly net present cost, operating cost, and LCOH—are the dominant factors distinguishing high- and low-ranked alternatives. This finding suggests that, even under favorable renewable conditions, economic feasibility remains the main barrier to large-scale green hydrogen deployment. Overall, the proposed approach enhances transparency in hydrogen system planning by clearly separating physical system simulation from decision analysis. Rather than producing black-box optimal solutions, it allows trade-offs to be explicitly observed and interpreted. The framework therefore offers a practical and transferable decision-support tool for the design of cost-effective and sustainable on-grid green hydrogen systems.

References

Bhandari, R., & Adhikari, N. (2024). A comprehensive review on the role of hydrogen in renewable energy systems. *International Journal of Hydrogen Energy*. doi:10.1016/j.ijhydene.2024.08.004

Buttler, A., & Spliethoff, H. (2018). Current status of water electrolysis for energy storage, grid balancing and sector coupling via power-to-gas and power-to-liquids: A review. *Renewable and Sustainable Energy Reviews*, *82*, 2440–2454. doi:10.1016/j.rser.2017.09.003

Dufo-L'opez, R., & Bernal-Agust'in, J. L. (2008). Multi-objective design of PV–wind–diesel–hydrogen–battery systems. *Renewable Energy*, *33*(12), 2559–2572. doi:10.1016/j.renene.2008.02.027

Egeland-Eriksen, T., Hajizadeh, A., & Sartori, S. (2021). Hydrogen-based systems for integration of renewable energy in power systems: Achievements and perspectives. *International Journal of Hydrogen Energy*. doi:10.1016/j.ijhydene.2021.06.218

Franzmann, D., Schmid, E., & Sterner, M. (2023). Green hydrogen cost-potentials for global trade. *International Journal of Hydrogen Energy*. doi:10.1016/j.ijhydene.2023.05.012

Glenk, G., & Reichelstein, S. (2019). Economics of converting renewable power to hydrogen. *Nature Energy*, *4*, 216–222. doi:10.1038/s41560-019-0326-1

Lambert, T. W. (2005). Micropower system modeling with HOMER. In *Integration of Alternative Sources of Energy*. John Wiley & Sons. doi:10.1002/0471755621.ch15

Opricovic, S, & Tzeng, G.-H. (2004). Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. *European Journal of Operational Research*, *156*(2), 445–455. doi:10.1016/S0377-2217(03)00020-1

Opricovic, Serafim, & Tzeng, G.-H. (2007). Extended VIKOR method in comparison with outranking methods. *European Journal of Operational Research*, *178*(2), 514–529. doi:10.1016/j.ejor.2006.01.020

Pohekar, S. D., & Ramachandran, M. (2004). Application of multi-criteria decision making to sustainable energy planning—A review. *Renewable and Sustainable Energy Reviews*, *8*(4), 365–381. doi:10.1016/j.rser.2003.12.007

Staffell, I., Scamman, D., Velazquez Abad, A., Balcombe, P., Dodds, P. E., Ekins, P., … Ward, K. R. (2019). The role of hydrogen and fuel cells in the global energy system. *Energy & Environmental Science*, *12*, 463–491. doi:10.1039/C8EE01157E

Steward, D., Ramsden, T., & Zuboy, J. (2009). *Lifecycle Cost Analysis of Hydrogen Versus Other Technologies*. Golden, CO, USA.