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Review of mathematical programming models for energy-based industrial symbiosis networks

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ABSTRACT

Formation of energy-based industrial symbiosis networks (EISNs) is a measure by which industries can address their high energy consumption. EISNs are often designed through mathematical programming (MP) because this method can represent the integration of numerous entities in a compact model while allowing tradeoff analysis of various EISN design objectives. In view thereof, this study presents a systematic review of MP models for EISN optimization. It addresses the research gap on the lack of studies which review the use of MP for optimizing EISNs involving waste heat as the shared resource. The models were analyzed based on five features: the typology of objective functions, the integrated entities in the EISN, the waste heat use options, the effects of considering distance between entities, and the method for modelling parameter uncertainty. This study has uncovered several gaps in EISN modelling. First, there is no consensus about the most relevant environmental and social impacts to include in EISN optimization. Second, novel approaches to simplify nonconvex models are scarce, thereby hindering the incorporation of more pertinent entities into the models due to the concomitant increase in solution time. Third, models analyzing the tradeoff among the various waste heat utilization pathways are limited. Fourth, most models do not include the implications of considering the physical layout of integrated entities in optimizing EISN design. Finally, the best method to incorporate parameter uncertainty in models is still unsettled. By addressing these gaps, more comprehensive MP models can be developed, thereby supporting better-informed decisions about EISN establishment.

Nomenclature

Abbreviations	
ARS	Absorption refrigeration system
CACRS	Combined absorption compression refrigeration system
EISN	Energy-based industrial symbiosis network
HEN	Heat exchange network
LMTD	Log mean temperature difference
LP	Linear programming
MILP	Mixed integer linear programming
MINLP	Mixed integer nonlinear programming
NLP	Nonlinear programming
MP	Mathematical programming
ORC	Organic Rankine cycle
SWS	Stage-wise superstructure
TES	Thermal energy storage

1. Introduction

Industrialization has significantly increased the world's energy consumption in recent decades. Estimates have shown that 40 % of the world's energy demand comes from the industrial sector [1], wherein majority of the consumed energy is used for process heating [2]. However, the industrial sector's use of energy is largely inefficient. The

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amount of waste heat that is discharged by heavy manufacturing industries to the environment is estimated to be 20–50 % of their total input energy [3]. This translates to around 8.45 TWh of unutilized waste heat generated by the global industrial sector annually [4].

To address the industrial sector's high energy consumption and wastage, two options can be explored. The first is for industries to ensure that all their equipment is operating at the highest possible energy efficiency rate. The second is for a plant to form an energy-based industrial symbiosis network (EISN) with other plants by sharing their waste heat with one another.

The implementation of energy efficiency measures is a strategy that individual companies can perform on their own. This includes the replacement of old equipment with more energy-efficient ones and periodic equipment maintenance or refurbishment. In addition, improvement of process control [5] by employing Industry 4.0 (4IR) technologies, such as smart sensors [6], can also help in optimizing industrial energy use.

Aside from these, heat management in the form of transferring excess heat from one process to another is also a key energy efficiency measure [5]. In the chemical and petroleum industries, this practice is referred to as heat integration [7]. Essentially, heat integration measures allow a hot process stream (which needs to be cooled down by a cold utility, such as cooling water from a cooling tower) to transfer excess heat to a cold process stream (which needs to be heated up by a hot utility, such as steam generated in a boiler), thereby resulting to a decrease in primary energy consumption by the utilities.

Heat integration modes can be either direct or indirect. Direct heat integration entails the use of a single heat exchanger in which a pair of hot and cold process streams exchange heat with each other. This is the ideal mode of heat recovery because it entails lower capital costs and results to higher heat recovery [1]. In contrast, indirect heat integration involves the use of an intermediate heat transfer fluid which absorbs heat from the hot process stream in one heat exchanger and then brings this heat to the cold process stream in another heat exchanger. This mode entails higher capital expenditures due to the need for multiple heat exchangers and extensive pipeline networks. However, this has the advantage of matching two process streams that cannot be in direct contact with each other due to long distances or safety concerns.

It must be underscored that heat integration allows waste heat to be used in other ways besides simple heat cascade. One approach is to upgrade the waste heat stream into a higher temperature stream by using heat pumps, mechanical vapor compression units, or absorption heat pumps. Another is to convert it to cooling energy by using absorption or adsorption chillers. Finally, waste heat can also be used to drive an organic Rankine cycle (ORC) or Kalina cycle plant to produce electricity. Among these technologies, the most widely used types in the industry are ORCs, heat pumps, absorption chillers, and heat exchangers [8].

Another way by which industries can reduce its primary energy consumption is the establishment of an energy-based industrial symbiosis network (EISN). This measure is complex because it requires individual companies, which may have competing interests, to cooperate with one another. Therefore, participating in an EISN is an option that industries can choose once they have exhausted all energy efficiency measures that they can implement on their own.

A classification method has been proposed by Afshari et al. [9] to categorize EISNs based on the level of cooperation among the participating entities. As shown in Fig. 1, Type "A" EISNs are networks in which waste heat is recovered and supplied back into the entity to be reused for its own internal processes. This is reminiscent of an intra-plant heat integration measure in which process streams belonging to a single entity are the only eligible candidates that can be matched to undergo heat exchange. Alternatively, type "B" EISNs are networks in which energy hubs are installed by the participating entities or by a third-party stakeholder to supply a portion of their energy demand. Fig. 2 provides a schematic diagram of a usual type "B" EISN. Finally,

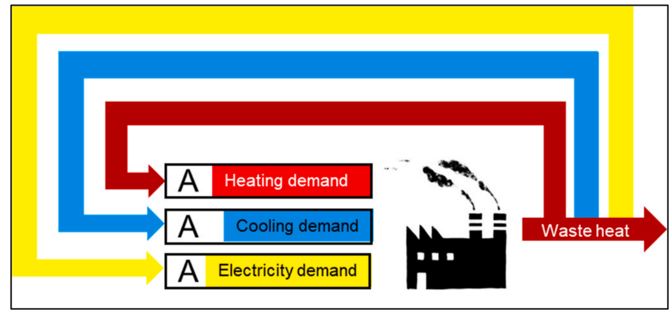

Fig. 1. A type "A" EISN in which a plant reuses waste heat to satisfy a portion of its heating, cooling, and/or electricity demand.

type "C" EISNs are networks in which excess heat is shared by one firm to other entities, as shown in Fig. 3. A specific instance of this is inter-plant heat integration wherein process streams from different entities can be matched with each other. A list of existing EISNs can be found in Table 1 which shows that the most common type of EISN is a Type "B" network. The probable reason behind this is that in a Type "B" network, the plants still have a high level of independence in their operations since the energy that they procure from the shared facilities does not depend on the fluctuations in the production levels of other plants.

Due to its highly collaborative nature, establishing a Type "C" EISN can significantly impact how the participating entities manage their energy use. It requires the entities to adopt a unified energy management system in which their respective energy policies are aligned with their intentions for participating in the EISN. These intentions must be overtly articulated right from the start of the design stage to ensure that the energy use and emissions reduction targets that the entities have set would eventually be realized. Since the energy management system prescribed by ISO 50001:2018 is based on the Plan-Do-Check-Act continual improvement framework [31], considering the participating entities to belong to a single organization can reduce the complications of enforcing the framework across multiple disparate entities. This is crucial when it comes to the 'Check' phase of the PDCA cycle, in which each entity's energy performance is audited. In this case, a heat sink plant must be able to demonstrate that it has indeed sourced a target portion of its heating requirements from its partner heat source plant/s. Conversely, the heat source plant must also be able to prove that it has supplied its pledged amount of waste heat to the EISN according to its energy policy.

The approach employed to establish an EISN largely affects the choice of EISN design method. A top-down approach is usually facilitated by a central decision-maker who, together with the collaborating entities, sets the objectives for forming the EISN and determines the EISN design constraints. This approach is best used at the early stages of a greenfield eco-industrial park development. A commonly used EISN design method under this approach is optimization through mathematical programming (MP). Conversely, a bottom-up approach is usually facilitated by the collaborating entities themselves to advance their respective interests. Game theory and agent-based modelling are the most frequently used methods under this approach [32]. It must be noted; however, that a synergy of methods can be used to enhance the resulting EISN design, similar to what was done in Ref. [33] in which game theory models in the form of Nash equilibrium constraints were incorporated in the MP model to determine the optimum trade price for the heat transferred by a source plant to a sink plant. More applications of game theory in EISN optimization can be found in Section 3.6 of th is review.

Several review articles related to industrial symbiosis network (ISN) modeling have been published. For instance, Demartini et al. [34] discussed the various quantitative approaches used to represent and analyze an ISN such as agent-based modelling, life-cycle assessment,

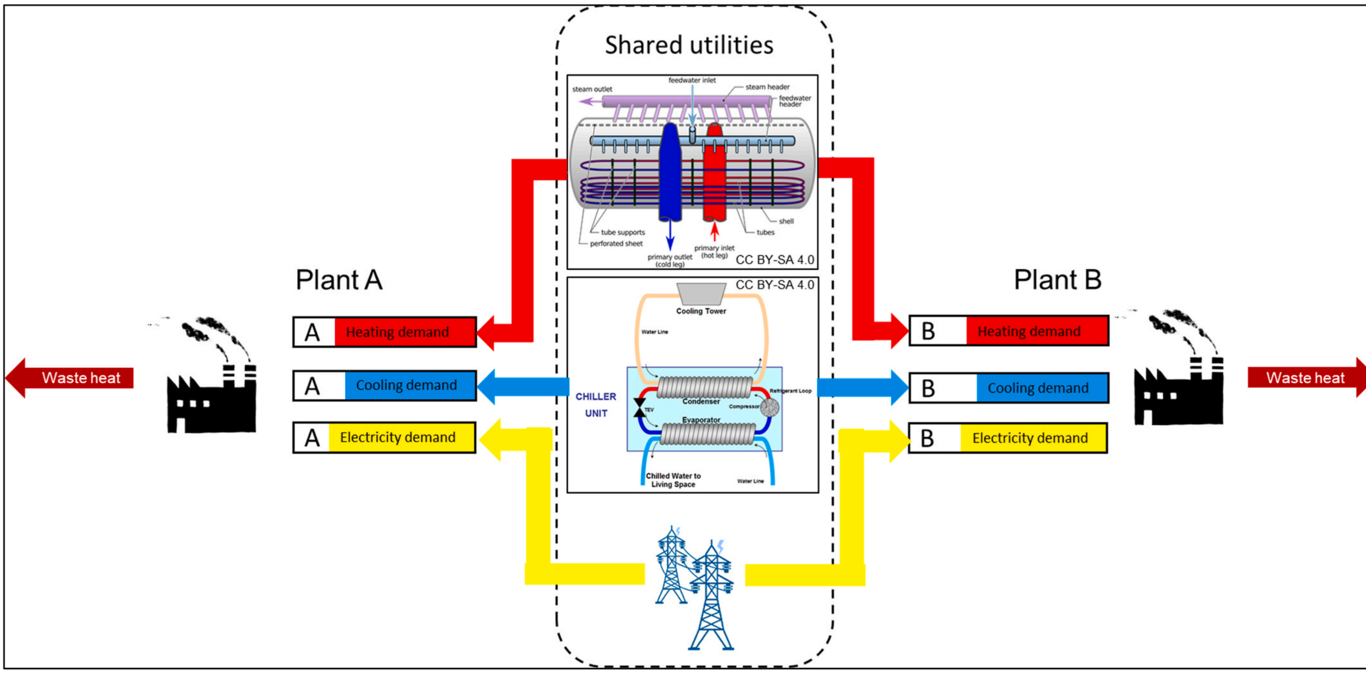

Fig. 2. A type "B" EISN in which two plants share a common heating utility (steam from a steam generator), a common cooling utility (cooling water from a cooling tower), and a common electric utility (electricity from a microgrid).

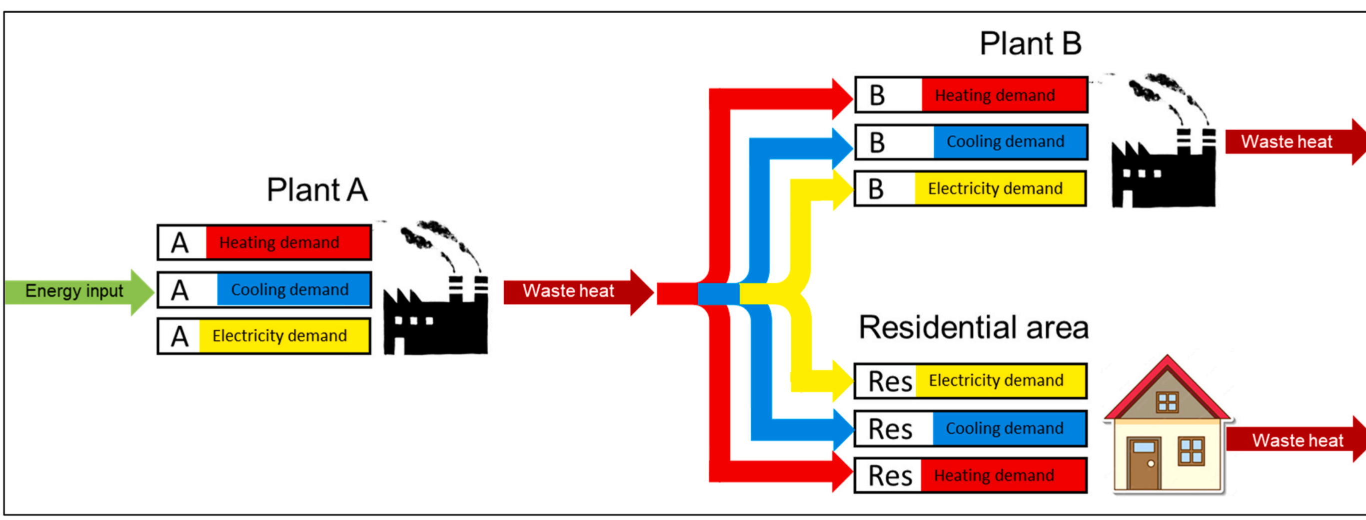

Fig. 3. A type "C" EISN in which a heat source plant (Plant A) supplies its waste heat to a heat sink plant (Plant B) and to a residential area to satisfy a portion of their heating, cooling, and/or electricity demand.

material flow analysis, network analysis, mixed integer linear programming, and system dynamics. They concluded that a hybrid approach of agent-based modelling and system dynamics is the best approach to model and simulate ISNs. However, they ignore the possibility that a bespoke modelling approach may be more suitable to be employed depending on the type of shared resource (i.e., material, energy, water, etc.) within the network and on the development stage at which the ISN is already in (i.e., design stage, operation stage). Somewhat similar to Ref. [34] is the work by Sodhi et al. [35] in which they presented various techniques to mathematically represent ISNs and discussed each technique's applicability to address various ISN design requirements (i.e., inclusion of various sustainability criteria, uncertainty modeling, incorporation of multiple types of resource exchanges, etc.). Although this study has identified MP as a suitable method for designing ISNs, it has considered this method to be inappropriate in accounting for the social dimension of ISN creation. Such insight is contrary to some of the cited studies in Section 3.1 of this research in which various forms of the social objective function have been incorporated in the EISN MP model. Other similar studies to Ref. [34] are found in Ref. [36], which focused its discussion on determining the ISN development stage at which optimization-based methods, game theory, and agent-based modelling is more suitable to be used. Further, Yazıcı et al. [37] discussed the exact methods, heuristic methods, multi-criteria decision analysis techniques, and simulation methods used to represent and analyze ISNs. However, the scope of the review in Ref. [37] is limited to identifying the type of MP model for ISN optimization (i.e., linear programming, integer programming, etc.) and the types of constraints and objective functions that are embedded in these MP models. In addition, Yazıcı et al. [37] has not identified the type of shared resource in the ISNs that have been modeled in the reviewed studies.

Table 1
Features of currently operational energy-based industrial symbiosis networks in which waste heat is the shared resource.

Ref	Location	IS Programme/Eco-Industrial Park	EISN Type	Remarks
[10]	Denmark	Kalundborg Industrial Symbiosis	B	Waste heat is provided by the Asnæs Power Station
[11]	Netherlands	Rotterdam Harbor and Industry Complex	C	Waste heat is provided by the Shell plant in Pernis.
[12]	Sweden	Landskrona Industrial Symbiosis Programme	C	Waste heat is provided by lead battery recycling and steel dust recycling plants.
[10]	Finland	Uimaharju Industrial Park	B	Waste heat is provided by a combined heat and power plant located in the EIP.
[13]	Finland	Jyvaskyla city	B	The paper mill provides waste heat to a local greenhouse, while the plywood mill shares a boiler plant with the Saynatsalo suburb, which provides heat to the mill and to the suburb.
[14]	Finland	Harjavalta industrial park	C	Waste heat is provided by the Pori Lämpövoima Oy (Pori Thermal Power Plant) to district heating.
[15]	France	Havre Industrial Harbour-Park	B	The Sedibex chemical waste incineration facility which provides process steam to the industries within the park.
[15]	Netherlands	Biopark Terneuzen	C	WarmCO2 facilitates the delivery of waste heat coming from Yara, an ammonia and fertilizer plant, to a local greenhouse near the biopark.
[15]	Switzerland	Cimo-Monthey Chemical Park	B	A chemical waste incineration facility provides process steam to the industries within the park. This incineration facility is operated by Cimo, a joint subsidiary of the two major chemical plants in the park, BASF and Syngenta.
[15]	Sweden	Händelö Island	B	Waste heat is provided by a CHP plant to the district heating network and to the adjoining ethanol production plant.
[15]	Finland	Rantasalmi Eco-Industrial Park	B	Waste wood is delivered to a biomass power plant which provides heat and electricity to the EIP and to the adjoining residential area.
[16]	France	Port-Jérôme Industrial Park	B	A waste incineration facility managed by SEVEDE (Syndicate for the disposal and energy recovery of estuary waste). SEVEDE is administered by an inter-municipal committee consisting of members which come from various communities along the Seine River. Municipal waste is being burned off through the ECOSTU'Air Energy Recovery Unit. Then, the produced steam is transported to TEREOS, a chemical company located in the Port Jerome industrial park.
[17]	Germany	BASF Verbund site Ludwigshafen	B, C	Besides the three CHP plants located within the park which provides steam to the chemical industries, waste heat is also provided by the other industries operating within the park.
[18]	Germany	Infraleuna	B	A cogeneration power plant provides electricity and steam to the industries within the park. This powerplant is owned and managed by the Infraleuna industrial park manager.
[19]	Germany	Marl Chemical Park	B	Onsite cogeneration power plants (two gas-fired and one coal-fired) provide electricity and steam to the industries within the park.
[20]	Germany	Oberbruch Industry Park	B	The industrial park management operates a type "B" energy symbiosis network which provides steam and cooling media to the industries within the park.
[21]	Netherlands	Getec Park.Emmen	B	The industrial park management operates a type "B" energy symbiosis network which provides steam and cooling media to the industries within the park.
[22]	Poland	Wroclaw Industrial Park	B	The industrial park management operates a type "B" energy symbiosis network which provides steam to the industries within the park.
[23]	Switzerland	Geneva Industrial Park	B	The industrial park management operates a type "B" energy symbiosis network which provides heating energy to the industries within the park.
[24]	Switzerland	Getec Park Swiss	B	The industrial park management operates a type "B" energy symbiosis network which provides heating energy to the industries within the park.
[25]	China	Shenyang Economic and Technology Development Zone	C	Waste heat is provided by the three power plants operating within the industrial park and is cascaded to chemical, pharmaceutical, and construction material industries.
[26, 27]	China	Suzhou Industrial Park	B	The cogeneration plants provide steam to the industrial park. Then, the waste heat from the Dongwu gas-fired cogeneration power plant is used to drive the lithium bromide absorption refrigeration system in the Moon Bay cooling center to produce cooling energy for district cooling in the Moon Bay district. During winter, waste heat from the Dongwu power plant is cascaded to the Moon Bay district to serve its heating demands.
[28]	China	Tianjin Economic-Technological Development Area	B	The Binhai cogeneration power plant provides steam to the industries within the park and serves the district heating demands of the adjacent municipality.
[29]	South Korea	Onsan and Ulsan-Mipo Industrial Parks	C	There are 14 energy symbiosis networks present among the companies located in these two industrial parks.
[30]	Puerto Rico	Guayama Industrial Park	B	The cogeneration plant provides steam to the Chevron Philips refinery.

Furthermore, there are also review articles which focused on the application of life cycle assessment methodology in modelling ISNs, such as [38,39]. However, most of the reviewed case studies in these two studies involve material-based ISNs only. As opposed to this, Kastner et al. [40] discussed the methodologies to search for potential symbiotic exchanges among multiple entities and to optimize the configuration of ISNs for energy, water, material, and multi-resource exchange. Although Kastner et al. [40] has included studies to optimize the design of EISNs with waste heat as the shared resource, the discussion has been limited to the novel modelling approaches for EISN optimization that each study has propounded. Somewhat similar to Ref. [40] is the study of Lawal et al. [41] in which ISN MP models have been classified according to the nature of shared resource in the ISN. However, Lawal et al. [41] have cited only one study in which waste heat was the shared resource within the industrial parks and have limited their analysis to identifying the MP model's optimization objective. Another study that is quite similar to Ref. [40] is the work of Boix et al. [42], which has discussed the approaches to optimize ISNs for material, energy, water, and industrial waste heat exchange and has provided a typology of objective functions in the MP models. However, similar to Ref. [41], Boix et al. [42] has focused only on scrutinizing the formulation of the objective functions in the various ISN models. Finally, there are also review articles that focused specifically on EISN optimization approaches. One of these is [43] in which the various methodologies for EISN optimization have been discussed. However, this research has only provided an accounting of the number of studies which used each type of methodology. Another study of this kind is [44] which has discussed the major solution methods for the heat exchanger network (HEN) synthesis problem. The studies cited in Ref. [44] have also been categorized based on whether the scope of heat integration covers only a single plant or multiple plants and the type of solution algorithm employed to solve the model. However, this research has limited its analysis to characterizing the HEN MP models as either a simultaneous or sequential approach to solving the HEN synthesis problem. For those MP models categorized under a sequential approach, this study has also just identified the aspect of the HEN synthesis problem that each model has been designed to solve (i.e., minimum utility targeting, minimum required number of stream matches, minimum required heat exchanger area).

The preceding discussion shows that a scarcity exists in the extant literature for review studies that scrutinize model formulations for optimizing EISNs, specifically those which employ MP as the main optimization approach. The importance of MP in determining the optimal EISN configuration lies in its ability to represent a large-scale integration of numerous entities within an EISN using a compact mathematical formulation. In addition, unlike other design approaches, MP also allows the tradeoff among different EISN design objectives to be investigated. Thus, this study aims to systematically review the existing MP models for EISN optimization.

The novelty of this research lies on its detailed analysis of EISN MP model formulations, which is intended to be more comprehensive compared to the other EISN optimization review studies that have been published so far. This review goes beyond simply identifying and categorizing the optimization objectives in existing models. It also examines other aspects of EISN MP models which are relevant in adequately representing the actual physical setup and operational conditions of prospective EISN participants. It also critiques certain modelling strategies on whether these make sense from both mathematical and practical perspectives to ensure that existing EISN MP models not only conform to well-established theories and conventions but can also yield logical and actionable insights on EISN formation.

To enable a more in-depth analysis of EISN MP model formulations, the following questions are answered in this study.

Main question: What are the mathematical programming models that have been formulated to optimize energy-based industrial symbiosis networks?

Specific questions.

1. What are the objective functions considered in the EISN MP models?
2. How is waste heat utilized in the EISN MP models?
3. What are the entities integrated in the EISN MP models?
4. How is the effect of distance between entities accounted for in the EISN MP models?
5. How is the uncertainty of input parameters accounted for in the EISN MP models?

The significance of this study lies on the fact that by analyzing the formulation of existing EISN MP models, future research could be geared toward developing more comprehensive MP models which can support better-informed decisions about the establishment of highly complex EISNs.

2. Methods

The literature search for studies related to EISN optimization was performed using three academic databases: Compendex, Scopus, and Web of Science. The keywords for the search centered around two main concepts: "energy or heat based industrial symbiosis" and "optimization". Table 2 shows the search words used in each database.

The search results were limited to articles which underwent peer review. In the Compendex database, only journal articles, conference proceedings, and conference articles were considered. In the Web of Science database, only journal, proceeding, and review articles were included. Lastly, in the Scopus database, only journals, conference proceedings, and books were considered.

Then, the PRISMA 2020 reporting guideline was used to methodically screen the studies collated from the literature search. The PRISMA 2020 flow diagram which served as the guide for the literature screening strategy employed in this study can be seen in Fig. 4.

The 5280 articles that were initially collected were first filtered using the following filtration criteria (FC).

FC 1: Study is not a duplicate.
FC 2: Study is written in English.
FC 3: Full text of the study is available.

After applying these filtration criteria, 4075 articles were left for further assessment. The following eligibility criteria (EC) were used to screen the remaining studies.

EC 1: The study involves industrial waste heat recovery. Recovery of other wastes, by-products, or other forms of energy (i.e., pressure energy) is not considered.
EC 2: The study involves a formulation of a mathematical programming model for the optimization of a waste heat exchange and/or utilization network among discrete entities or within the entity from which the waste heat originates.
EC 3: The study provides a conceptual model describing the formulation of the objective function(s) and constraints and an explanation of the mathematical notations used in the mathematical model to clearly distinguish parameters from decision variables.

After applying the study filtration and eligibility criteria stipulated in the PRISMA 2020 flow diagram, only 72 studies were left to be included in this review. Finally, snowball sampling was performed to identify studies that were not part of the search results but satisfied the three eligibility criteria. In total, 80 studies were deemed eligible to be part of this systematic review.

As a final note, a likely source of error for this systematic review is the selection bias that comes from the choice of keywords for the literature search. Table 2 shows that "energy or heat integration" is included as part of the search words. As explained in Section 1, heat integration is an energy efficiency initiative that is mostly practiced in chemical and petroleum industries. Due to this, the literature search for this systematic review may be biased towards studies that cover heavy manufacturing industries. Therefore, only a few EISN optimization studies that deal with light manufacturing industries may have been included in this review.

3. State-of-the-art of EISN MP modelling

3.1. Objective functions in EISN MP models

The choice of objective function in an EISN MP model largely reflects the priority placed by the stakeholders during the design of an EISN. For instance, heat integration MP models covering single or multiple plants have been traditionally concerned with either the cost-optimality of the resulting EISN or the minimum required external utility consumption needed to satisfy the heating and cooling needs of an entity. Thus, most early EISN MP models have just incorporated economic or thermodynamic functions as their optimization objectives. But with the growing emphasis placed on sustainability at the turn of the 21st century, environmental and some social optimization objectives have started to be overtly incorporated in recent EISN MP models. The chronology of how the typology of the optimization objectives in EISN MP models has evolved over time can be seen in Fig. 5. This timeline is not intended to contain an exhaustive list of all iterations of objective functions in EISN MP models. Instead, it is meant to show that the basis for the attractiveness of such energy efficiency initiative has no longer just been its economic and thermodynamic viability, but rather has extended to its ecological and societal benefits over time.

Fig. 6 shows the prevalence of single-objective EISN MP models involving economic objective functions. Since most EISN MP models are related to heat integration, the typical objective in these models is the minimization of the total EISN costs. The usual components of the

Table 2
Keywords used in each database during the literature search.

Database	Keyword statement
Scopus	(TITLE-ABS-KEY ((waste OR surplus OR lost OR "low grade" OR "low temperature") W/3 heat)) AND (((TITLE-ABS-KEY ((energy OR industrial) W/3 symbiosis) OR TITLE-ABS-KEY ((energy OR heat) W/3 integration))) OR (TITLE-ABS-KEY ("industrial park"))) AND (TITLE-ABS-KEY (optim*))
Web of Science	((waste OR surplus OR lost OR "low grade" OR "low temperature") NEAR/3 heat (Topic) and ((energy OR industrial) NEAR/3 symbiosis) OR ((energy OR heat) NEAR/3 integration) OR "industrial park" (Topic)) AND (optim* (Topic))
Compendex	((((((waste OR surplus OR lost OR "low grade" OR "low temperature") AND heat) WN KY) AND ((((energy OR industrial) AND symbiosis) OR ((energy OR heat) AND integration) OR "industrial park") WN KY))) AND ((optim*) WN KY)

economic objective function are the energy consumption costs of the hot and cold utilities, and the fixed and area costs of the heat exchangers needed to satisfy the minimum required utility consumption.

Combining these three cost components in a single objective function was first done in the seminal three-part study of Yee et al. in Refs. [45, 46], and [47]. This series of studies was the first to formulate an MINLP model based on a stage-wise superstructure (SWS) that can simultaneously determine the minimum energy targets for hot and cold utilities, the minimum number of heat exchangers needed to meet these targets, and the optimal area of each heat exchanger. Prior to this study series, only sequential approaches were proposed in earlier studies, such as [48, 49], and [50], to solve the HEN synthesis problem, which typically involve the use of a linear programming (LP) model for energy targeting, a mixed-integer linear programming (MILP) model to determine the minimum required number of connections between the process streams, and a nonlinear programming (NLP) model to determine the minimum required heat exchanger areas. Since then, several modifications to the simultaneous optimization approach have been made. These include the ones in Refs. [51,52] in which the SWS-based MINLP model was replaced by an interval-based superstructure MINLP model. Another modification to the simultaneous optimization approach was done by Wu et al. in Ref. [53] in which the SWS-based MINLP model was reformulated into an NLP model. This was done by approximating the value of binary variables which indicate the presence of a heat exchanger between hot and cold process streams using nonlinear constraints, thereby eliminating the need for big-M constraints. This strategy is noteworthy because inappropriate estimations on the big-M values can adversely affect an MP model's feasibility.

Other cost functions have also been considered in the economic objective function. For instance, the MINLP models in Refs. [54–61], and [62], which have thermodynamic cycles in the HEN, have also added the capital and operating costs of each cycle component (i.e., turbine, pump, compressor, absorber, etc.). Another cost type is maintenance cost which Oluleye and Smith [63] assumed to be 2 % of an equipment's capital cost in their MILP model. Lastly, an often-ignored cost type is the cost of splitting process streams that can only be found in the MINLP model formulated by Angsutorn et al. in Ref. [64]. Incorporating this cost is crucial when investigating the tradeoff between attaining higher rates of heat recovery from matching split streams and the accompanying costs of splitting process streams. This cost type is not included in most heat integration studies, probably because representative values are rarely found in published literature. In fact, as surmised from the acknowledgement section of [64], the value of this cost may have been sourced from the advice of process engineers in the gas separation plant that was the subject of this study; thereby, making the value of this cost highly context-specific.

Besides the minimization of total costs, some economic objectives involve maximization of savings or profit attained from participating in an EISN. For instance, Bagajewicz and Barbaro [65] maximized the savings in utility consumption in their NLP model after integrating a

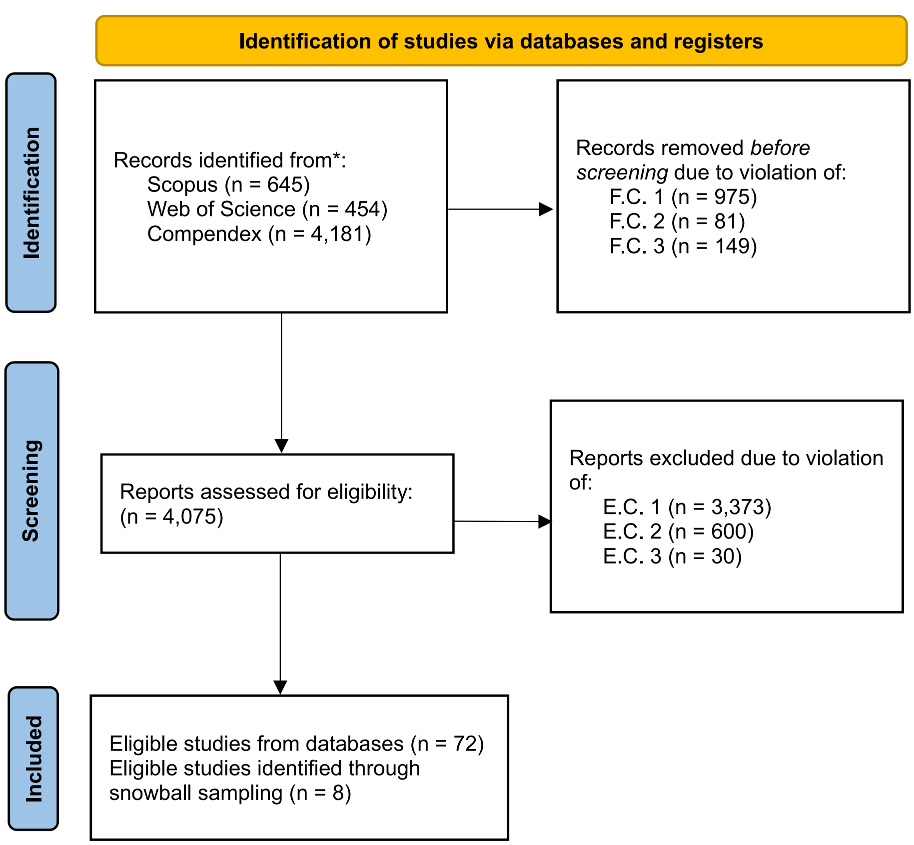

Fig. 4. Study screening flow chart.

heat pump in the HEN. In addition, Angsutorn et al. [64] and Kovač Kralj and Glavič [66,67] maximized net profit in their MINLP models by subtracting the costs of all heat recovery equipment from the savings in utility consumption. Finally, net profit was maximized in the MINLP models of Seid and Majozi [68] and Lee et al. [69] by computing the difference between the revenue from the sale of a plant's products and the utility costs.

The next most predominant single-objective EISN MP model involves those with a thermodynamic objective function. One such objective is the minimization of the number of heat exchangers in the HEN, such as in Ref. [67]. Another is the minimization of the energy consumption from external utilities, such as in the LP and MILP models formulated by Rodera and Bagajewicz in Ref. [70]. Furthermore, Chen and Ciou [71] considered the minimization of the TES tank volume in their MINLP model to enable indirect heat integration in a batch processing plant. Finally, Gu et al. [72] formulated a MILP model to minimize the exergy destruction of hot process streams within a crude oil distillation unit (CDU) from which surplus heat were recovered to generate steam that was used for indirect heat integration within the CDU.

Various cost functions corresponding to different aspects of EISNs have been considered in some multi-objective optimization studies. For instance, Becker and Maréchal [73] formulated a MILP model for the minimization of total operating costs and the minimization of heat exchanger area costs to generate a two-dimensional Pareto curve. Alternatively, Bütün et al. [1] formulated an inter-plant HEN MILP model in which two objectives were minimized, the sum of the operating and investment costs and the piping cost. The piping cost was considered as the epsilon-constraint (ε-constraint) for the generation of the Pareto curve.

Multi-objective optimization involving different types of objective functions can also be found in some EISN MP models. Some of these are bi-objective MP models with economic and thermodynamic objective functions. For instance, the MINLP model in Ref. [60] considered the minimization of the investment and operating costs of an ORC-integrated HEN and a combined absorption-compression refrigeration system (CACRS) with the profit from the sale of electricity generated by the ORC deducted as its economic objective, while the thermodynamic objective was the minimization of exergy destruction within all the HEN, CACRS, and ORC equipment. Exergy destruction was used as the ε-constraint in the study. Finally, the MILP model in Ref. [74] used the minimization of the total costs of an ORC-integrated EISN, with the revenue from the sale of electricity deducted, and the maximization of waste heat recovery as the dual objectives. Waste heat recovery was the ε-constraint in this study.

In addition, EISN MP models involving both economic and environmental objectives also exist. These models considered different environmental impacts. For instance, the MILP models in Refs. [75,76], and [77] minimized the sum of the emissions from the export of waste energy from source plants to sink plants and the emissions from the import of energy from outside the industrial park. A Pareto curve was generated in these studies by assigning different sets of weights to the economic and environmental objectives to investigate the tradeoff between these two objectives. In addition, Liu et al. [78] minimized the aggregate environmental impacts of fuel consumption by the hot utilities in their MINLP model. These impacts included greenhouse gas emissions, damage to human health due to climate change, and damage to resources due to fossil fuel extraction. The environmental objective was the ε-constraint in this study. Finally, the MINLP model in Ref. [79]

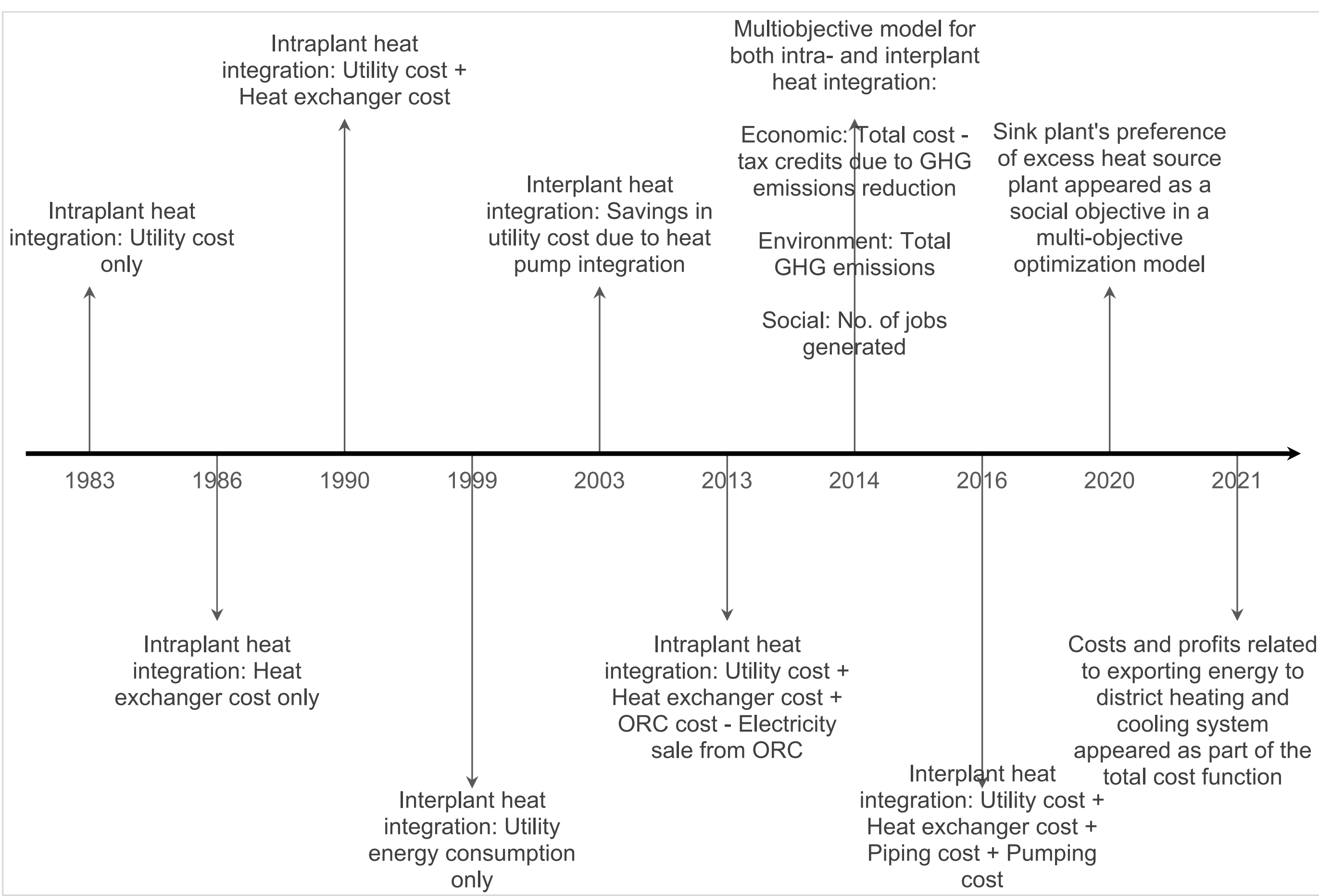

Fig. 5. Evolution of the typology of optimization objectives in EISN MP models.

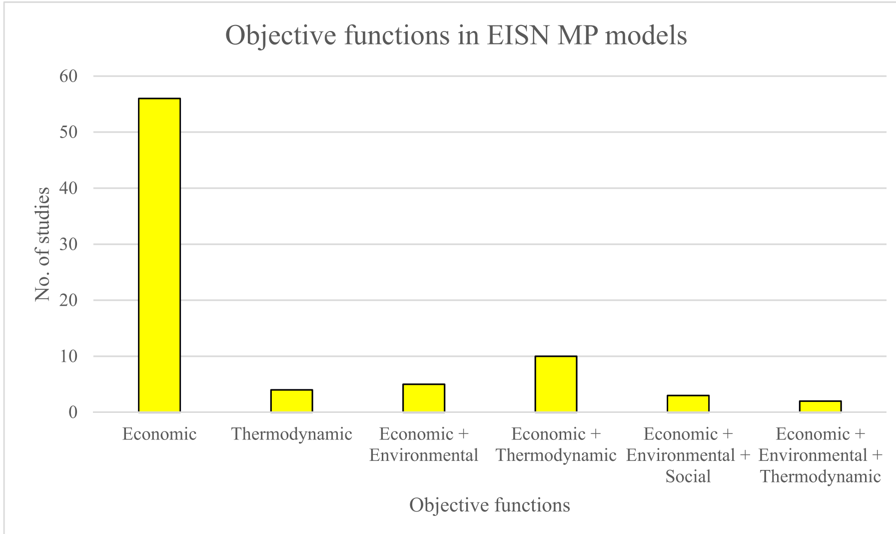

Fig. 6. Objective functions in EISN MP models.

maximized the CO_2 emissions reduction due to HEN retrofit. This was computed by subtracting the CO_2 emissions related to the installation of additional heat exchangers and the CO_2 emissions related to the compressor power consumption from the reduction in CO_2 emissions due to the savings in hot utility consumption. No information was given in this study regarding the method used to generate the Pareto front. However, the incorporation of emissions related to the construction and operation of waste heat recovery equipment in the model sheds new light on the tradeoff between attaining higher rates of heat recovery and the accompanying increase in CO_2 emissions due to the installation of additional heat recovery equipment. .

EISN MP models with three types of objective functions have also been formulated. An interesting subset involves those that considered economic, environmental, and social objectives. Only a few studies considered social objectives in their MP models. The number of jobs generated annually due to the establishment of an EISN was maximized in the MILNP model formulated by Hipólito-Valencia et al. in Ref. [55]. This study used the Jobs and Economic Development Impact (JEDI) model to account for the number of jobs created for each unit of energy produced by each energy source. A two-dimensional Pareto curve of the total annualized cost and total greenhouse gas emissions was created with the number of jobs generated at each Pareto-optimal solution indicated in the curve. Conversely, the MILP model formulated by Afshari et al. in Ref. [32] maximized a sink plant's preference for a waste heat supplier as its social objective. Analytic network process was used to quantify the sink plant's preference for an energy supplier based on the source plant's environmental practices, use of environmentally friendly technologies, and social contribution (i.e., number of jobs created, labor practices, etc.). A weighting method was used to generate three two-dimensional Pareto curves to investigate the tradeoff between each pair of objectives. Lastly, the MILP model formulated by Asghari et al. in Ref. [80] maximized the satisfaction level of a sink plant from sourcing its heat requirements from the available waste heat in the EISN and from maximizing the ORC energy generation capacity as its social objective. This study used the robust augmented ε-constraint method (AUGMECON-R) to generate the Pareto front.

As a final note, the terms in the objective function should always have similar units since neglecting to observe this may adversely impact the optimization results. However, the objective function of the MILP model in Ref. [81] lacks dimensional homogeneity among the combined terms. Costs (in \$), difference in heat duties (in kW), and temperature differences (in °C) were brutely added in the objective function without any normalization. In this regard, MP models must be formulated carefully to prevent this oversight.

3.2. *Waste heat utilization pathways in EISN MP models*

According to Benedetti et al. [8], there are four categories of waste heat recovery technologies based on how waste heat is reused. These are waste heat to heat (e.g., heat pumps), waste heat to cold (e.g., absorption chillers), waste heat to power (e.g., organic Rankine cycle plants), and heat exchange or simple heat cascade (e.g., heat exchangers and thermal energy storage). Through this technology categorization, industrial waste heat can therefore be thought of as a "primary energy" which can be transformed to other forms of energy within an EISN. Framing waste heat in this manner is significant because it allows EISN designers to explore multiple possibilities by which available industrial waste heat can be maximized to help fulfill the various energy demands of the EISN participants, subject to the thermodynamic limits of such endeavor.

Fig. 7 shows that waste heat cascade is the predominant waste heat use option in an EISN. This is because most EISN MP models are based on heat integration studies, which historically only explored the transfer of excess heat from hot process streams to cold process streams to reduce utility consumption. Furthermore, heat cascade is simpler to implement because heat exchangers are the only major equipment needed, as compared to incorporating thermodynamic cycles which entail the installation of other equipment such as turbines, compressors, and pumps. However, considering only one waste heat use option can limit waste heat recovery and discourage plants from participating in an EISN, especially when the costs of enabling a selected option are deemed uneconomical.

Various EISN MP models considered the use of waste heat for purposes other than simple heat cascade. For instance, the model in Ref. [82] allowed waste heat from different plants to drive a centralized ARS which provided chilled water back to the plants. Alternatively, the model in Ref. [83] allowed indirect integration of multiple parallel ORCs in a HEN. Finally, MP models that only considered heat pump integration can be found in Refs. [65,84], and [85]. The scopes of these three studies vary. For instance, Bagajewicz and Barbaro [65] developed an iterative approach to determine the optimal temperature for waste heat recovery by a single heat pump within a temperature interval below the combined pinch point of multiple plants and the optimal temperature for waste heat transfer by the heat pump within a temperature interval above the combined pinch point. Conversely, Oluleye et al. [84] developed an LP model which allowed waste heat to be recovered from the cooling utilities instead of the hot process streams. Furthermore, this model allowed for the selection of the best waste heat upgrading technology among mechanical heat pumps, absorption heat transformers, and absorption heat pumps. Lastly, Hu et al. [85] incorporated a flash tank in the MINLP model to recover the vapor portion of the two-phase steam that served as the intermediate heat transfer fluid for waste heat recovery from hot process streams. Only the vapor portion of the steam was fed into the heat pump.

Models that considered two waste heat use options have also been formulated. Most of these include waste heat cascade and electricity production from ORCs. Different approaches have been employed to model and incorporate ORCs in these models. For instance, although Hipólito-Valencia et al. [54] and Kovač Kralj et al. [66] extended the SWS-based MINLP model in Ref. [46] to incorporate ORCs in the HEN, the former only let the ORC streams to recover heat from the hot process streams at the last stage of the superstructure before the cooling utilities, while the latter allowed the ORC streams to exchange heat with the hot process streams at any stage of the superstructure. In addition, the model in Ref. [66] considered ORC turbine efficiency as a dependent decision variable that is correlated with the turbine inlet temperature, an independent decision variable, while, the model in Ref. [54] treated the ORC turbine and pump efficiencies as input parameters. Another difference between these two studies is that the model in Ref. [54] allowed the cold process streams to cool down the ORC working fluid at the turbine exhaust while letting the ORC working fluid at the turbine exhaust to preheat the ORC working fluid at the pump outlet inside a regenerator. The MP model in Ref. [66] did not have these two features. Besides these two studies, another notable study is [61] due to the novel approach by which it addressed the long computational time for solving the HEN-ORC integration problem. Like in Refs. [54,66], Liu et al. [61] also extended the SWS-based MINLP model in Ref. [46] by also integrating an ORC in the HEN. It decomposed the HEN-ORC optimization model into two sub-problems. The first sub-problem involved minimizing the total cost of setting up the HEN only. The process streams that were not matched for direct heat integration in the optimal solution of the first sub-problem were then allowed to exchange heat with the ORC working fluid streams in the second sub-problem. The objective function of the second sub-problem is the same as that of the first sub-problem, but the scope of the MINLP model in the second sub-problem included the constraints related to the ORC components. Another noteworthy study which also extended the SWS-based MINLP model in Ref. [46] by integrating ORC in the HEN is [86]. But the novelty in this work is the incorporation of ORC configurations which involve either a combination or a stand-alone use of turbine bleeding and regeneration to increase ORC thermal efficiency.

EISN MP models that considered three waste heat utilization pathways involve those that allow waste heat cascade, production of cooling energy via ARS, and electricity production via ORC. These models include the ones in Refs. [55,59,60], and [87], all of which extended the SWS-based MINLP model in Ref. [46]. But they differ in how the ARS and ORC were integrated in the HEN. For instance, Hipólito-Valencia et al. [55] and López-Flores et al. [87] allowed the ORC and ARS to be incorporated at any stage within the superstructure. They also let the hot process streams reach sub-ambient temperatures by allowing these streams to transfer heat to the ARS working fluid after being cooled down by the cold utilities at the end of the superstructure. It must be noted that the model in Ref. [87] extended the scope of [55] by incorporating a method for optimal profit allocation among the plants in an EISN. Conversely, Sun et al. [60] allowed for the CACRS generator and the ORC evaporator and condenser to exchange heat with the hot and cold process streams at any stage of the superstructure. In addition, the model also allowed the hot process streams to undergo two stages of refrigeration through absorption refrigeration and electric compression at the end of the superstructure after the cold utilities. Lastly, Ji et al. [59] allowed for the simultaneous optimization of intra-plant direct heat integration, inter-plant indirect heat integration, and the integration of various waste heat recovery cycles (WHRCs), such as ARS and ORC, within the HEN. The WHRC systems were integrated in the HEN under two modes: a centralized mode and a distributed mode. Centralized WHRC referred to the configuration in which the WHRC system is located either at the plant with the greatest cooling load or at a central location to which various plants can export their excess heat via indirect heat integration. Alternately, distributed WHRC referred to the configuration in which each plant had its own WHRC systems. Results of this study have shown that a distributed WHRC configuration was preferable in cases where the sum of the utility consumption costs, piping costs, and pumping costs dominated the total EISN costs. Otherwise, if the capital costs of the heat exchangers and the WHRC components dominated, a centralized WHRC configuration was preferred.

The only EISN MP model that considered the four waste heat use options is the MILP model in Ref. [63]. This model simultaneously optimized waste heat recovery from both the hot process streams and cold utilities and determined the best waste heat use option. The waste heat utilization technologies considered in this study were ORC, ARS, absorption heat transformers, absorption heat pumps, and mechanical heat pumps. Although the proposed approach was able to determine the optimal use case for a waste heat stream based on its temperature, the optimal stream matches for heat exchange and the optimum HEN configuration cannot be determined by the model.

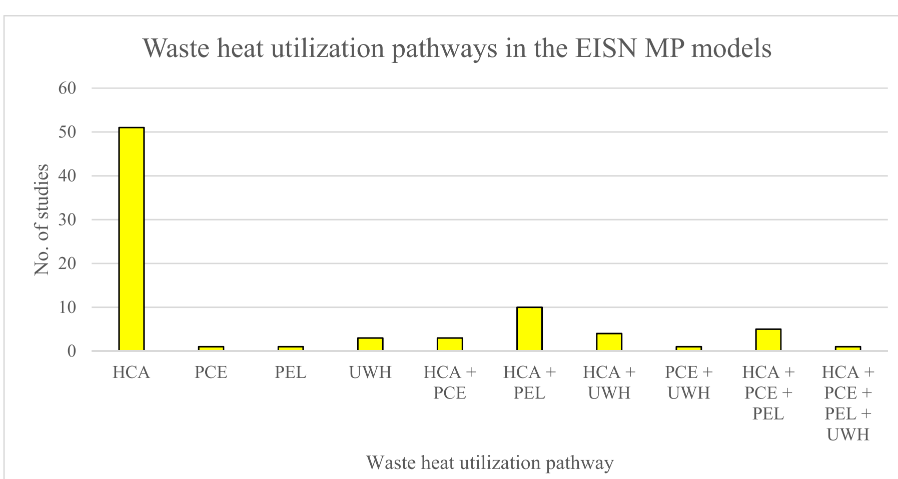

Fig. 7. Waste heat utilization pathways in EISN MP models. Legend: HCA – heat cascade; PCE – production of cooling energy; PEL – production of electricity; UWH – upgrading of waste heat to a higher temperature stream.

3.3. Integrated entities in EISN MP models

As discussed in Section 1, the types of entities that are integrated in an EISN depend on the level of willingness that individual entities have in shouldering the financial and operational risks of establishing an EISN, whether it is just an intra-plant initiative or requires the collaboration of other entities. Although intra-plant heat integration (Type "A" EISN) seems to be the easiest type of EISN to establish, this may not be the case for non-continuous processing plants because the hot and cold process streams that are to be heat integrated may not exist simultaneously all the time. In this case, a thermal energy storage (TES) system must be put in place, in addition to heat exchangers, so that excess heat from a hot process stream may be transferred both spatially and temporally to a cold process stream. However, the financial viability of integrating low-grade TES in an EISN must be thoroughly assessed since the cost-effectiveness of TES still remains a challenge from both engineering and economic perspectives [88]. Another option for entities that intend to reap the advantages of EISN participation is to share the costs of setting up waste heat recovery cycle plants, such as ORC and ARC, to which they can export their waste heat so that it can be transformed to either electricity or cooling energy. In this case, a Type.

"B" EISN is formed and the participating entities can receive the benefit of sourcing a portion of their power or cooling needs from these waste heat recovery cycle plants. Finally, industrial entities can choose to intimately align their operations by sharing their waste heat with one another in a Type "C" EISN. Although connecting as many plants as possible can be demonstrated to be feasible from a thermodynamic perspective, maintaining the control and safety of such complex heat integration scheme is practically challenging. This is the reason why Song et al. [89] have proposed to limit the number of entities in a single inter-plant heat integration scheme to a maximum of three. Alternatively, industrial entities can also opt to form a Type "C" EISN by exporting their excess heat to the district heating and/or cooling systems of nearby urban areas, thereby forming an urban-industrial symbiosis network. This is similar to the setup in an eco-industrial park in South Korea in which the Busan Fashion Color Industry Cooperative (BFCIC) operates a combined heat and power plant which supplies steam to the Busan Fashion Color Industrial Park (BFCIP) during daytime and redirects surplus steam to a nearby residential apartment complex during nighttime [90].

Fig. 8 shows the type of EISN modeled in the various MP models. This figure shows that most EISN studies only consider intra-plant heat integration, thereby making Type "A" EISN as the most widely optimized EISN type. In addition, some Type "A" EISN models also include thermal energy storage (TES), but these models are limited to studies which involve batch processing plants, as seen in Refs. [71,91–93], and [94].

The only Type "B" EISN model considered in this study is the one in Ref. [82] in which multiple plants share a centralized absorption refrigeration system – vapor compression refrigeration system (ARS-VCRS) plant. The plants transfer waste heat to the ARS which then transfers cooling energy back to the plants. It must be noted that although other MP models for Type "B" EISNs also exist, such as [95–97], and [98], these were not considered in this study because these violated the first eligibility criterion stating that only studies that involve waste heat recovery from industrial or non-industrial entities are considered.

Most Type "C" EISN models consider only inter-plant heat integration, while some incorporate a common TES that is shared by multiple plants, as seen in Ref. [99]. Furthermore, some inter-plant heat integration models also allow industrial waste heat transfer to domestic heating systems, as seen in Refs. [32,74,75,100], and [101]. Alternatively, Zhang et al. [102] did not consider inter-plant heat exchange, but it allowed industrial waste heat to be exported to a district heating system during cold seasons and to drive an absorption refrigeration system (ARS) which provides cooling energy to a district cooling system during hot seasons. Lastly, the model formulated in Ref. [80] allowed for inter-plant heat integration with TES and waste heat export to non-industrial areas.

Models which optimize hybrid EISN types, such as those that simultaneously allow both intra-plant and inter-plant heat integration (hybrid Type A + C EISN), have been formulated in Refs. [33,59,103], and [104]. Although these models comprehensively account for different heat integration options, these models can also be very complex, especially as the number of process streams and plants increase. Therefore, to simplify the problem of simultaneous intra-plant and inter-plant heat integration, Song et al. [105] proposed the Nearest and Largest Q_{rec}-based Screening Algorithm which proceeds by performing intra-plant heat integration first then nominating the remaining non-integrated streams to undergo inter-plant heat integration.

3.4. Effect of distance between integrated entities

One of the important considerations for establishing an EISN is the proximity between the process streams to be integrated [106]. To demonstrate the importance of considering plant layout in EISN optimization, a hypothetical case study was presented in Ref. [106] which involved six processes that were served by a common hot utility. By basing the utility steam pressure only on the process streams' minimum steam pressure requirement, the required pressure at the main steam header was only 2 barg. But, when the horizontal distances and elevations of the process streams relative to the centralized hot utility have been considered, the steam header pressure requirement increased to 5.2 barg.

Fig. 9 shows that only 28 % of studies considered distance in their MP models. In relation to this, Fig. 10 shows that Type "C" EISN models are the most predominant type of MP models with distance consideration, while Type "A" EISNs are the most widely optimized EISN type in models without distance consideration. This is the case because historically, most heat integration studies often ignore plant layout in their analysis.

Although most Type "A" EISN MP models neglect distance between process streams, there are some which indirectly include distance in their heat integration approach. For instance, Becker and Maréchal [73] and Pouransari and Maréchal [107,108] used the concept of sub-systems to minimize the number of connections between hot and cold process streams. Grouping process streams into sub-systems can be performed based on arbitrarily set criteria, such as the proximity between process streams. In this case, only process streams belonging to the same sub-system can undergo direct heat integration, while those belonging to different sub-systems can only undergo indirect heat integration. However, determining the minimum distance required for process streams to belong to different sub-systems is based on the process designer's prerogative, thereby making this approach dependent on heuristic rules.

Studies that considered the effect of distance have different ways of treating this factor in their models. For instance, by treating inter-plant distances as exogenous model parameters, the models in Refs. [9,32,75,76], and [77] constrained the maximum distance over which two plants can form an EISN at 20 km. However, setting a maximum distance limit is a heuristic rule that is not based on energy balance or budget constraints. Thus, employing this approach cannot guarantee the actual thermodynamic and economic feasibility of the resulting EISN connections.

Considering distance leads to the inclusion of pipe cost, pumping cost, heat loss from pipelines, and/or pipeline pressure drop in the MP model. Fig. 11 shows the number of EISN MP models that considered each impact. This shows that pipe cost is the impact that is included in most MP models with distance consideration.

In this regard, there are various ways by which pipeline cost is calculated. The easiest method is to exogenously define the value of the pipeline cost per unit length, which is then multiplied to the distance

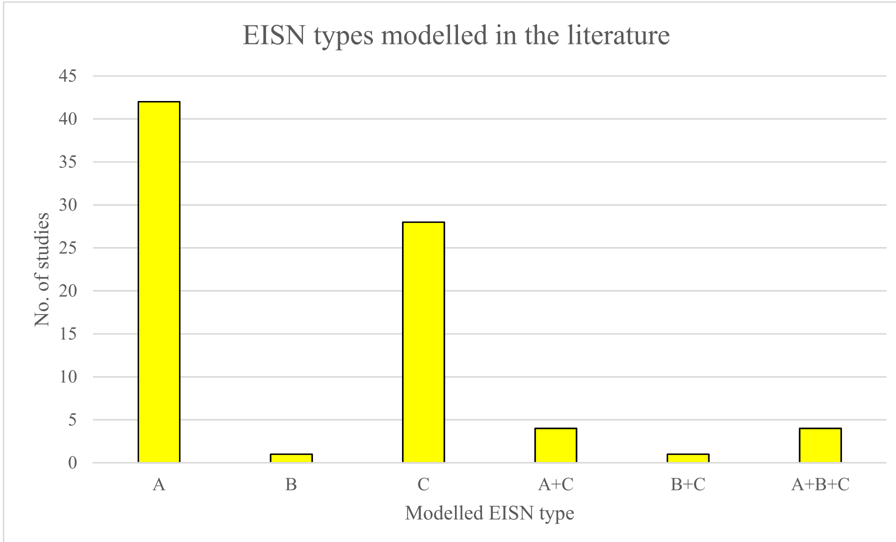

Fig. 8. Number of models for each EISN type in the literature.

between two entities and to the binary decision variable indicating the existence of a connection between the entities. This was done in Refs. [9,32,74–77,80,82,100], and [101]. Conversely, both Bütün et al. [1] and Kachacha et al. [109] defined the pipeline cost per unit length as a discrete function that is based on the pipe diameter, a decision variable which is a continuous function of the mass flow rate. Aside from these, the models in Refs. [7,102,103,105,110–112], and [113] correlated the pipe cost per unit length with the pipe diameter and weight, both of which are again decision variables that are continuous functions of the mass flow rate. Finally, a noteworthy method for calculating the total pipeline cost can be seen in Ref. [59] in which no pipe cost per unit length was defined. Instead, a polynomial regression equation was used to correlate the total pipeline cost to both the mass flow rate and the distance between the connected entities, thereby precluding the use of nonconvex equality constraints for the computation of pipe diameters and weights.

At the other side of the spectrum are those models that included all four impacts of considering distance. These models include the ones in Refs. [1,102], and [112]. As far as modelling heat loss is concerned, both Bütün et al. [1] and Zhang et al. [112] used the heat transfer coefficient of an insulated pipeline to compute for the temperature of the intermediate heat transfer fluid as it enters the sink plant from the source plant, and vice versa. Alternatively, Zhang et al. [102] assumed a heat loss rate of 1 % per unit kilometer of pipeline, as proposed by Kapil et al. [114]. Besides heat loss, the pumping power requirement computed in these MP models depended not only on pipe length but also on the pipeline pressure drop. Practically-speaking, this is a more comprehensive approach to pumping power computation, as compared to the one employed in Refs. [7,59] which based the pump pressure head only on the pipeline length.

Interestingly, Stijepovic et al. [110,111] also computed for the pipeline pressure drop but did not use this information in computing for the pumping power consumption. Instead, this was used as a parameter in one of the model constraints to determine whether the required heat stream pressure level of a sink plant could be satisfied if the waste heat stream came from a source plant, which produced waste heat at a certain pressure level.

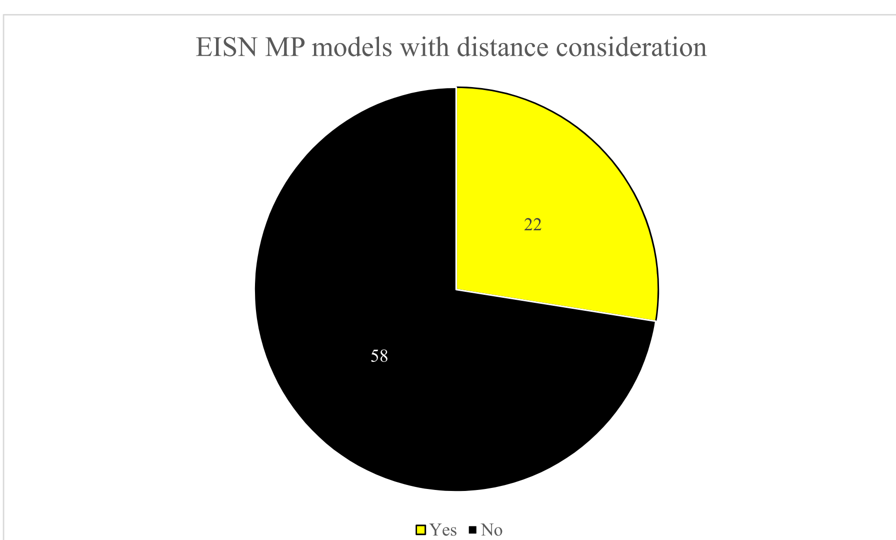

Fig. 9. Proportion of EISN MP models with distance consideration.

3.5. Incorporating parameter uncertainty in EISN optimization

Input parameters of EISN MP models can be categorized into two: process-level and plant-level. Models with process-level input parameters have more granularity compared to those which require only plant-level input parameters. This enables the former type of MP models to generate richer information about the architecture of the resulting optimum EISN configuration. The most common process-level input parameters are the supply and target temperatures of the hot and cold process streams, as well as their heat capacity flow rates. Conversely, plant-level input parameters typically include the temperature and flow rate of the heat streams that can be supplied by a source plant and that is demanded by a sink plant. Notice that each plant is already categorized as either a source plant or a sink plant at the start of the optimization process, which makes this information an exogenous input to the model, instead of being endogenously determined from the optimization results. In addition, models requiring plant-level input parameters assume that only one waste heat stream goes in or out of a plant, as compared to models with process-level input parameters which allow a plant to possess both hot and cold process streams. Fig. 12 shows the difference between these two categories of input parameters for EISN MP models.

In practice, the values of these parameters vary over time because industrial plants are expected to operate dynamically due to inherent process variability, planned or unforeseen plant shutdowns, or the need to vary production rates to respond to external market forces. However, Fig. 13 shows that 65 % of EISN MP models implicitly assume that industrial operations are static by simply using nominal values for the input parameters.

The risk of not considering parameter uncertainty in designing EISNs cannot be understated. For instance, computing the minimum required heat exchanger area based on nominal parameter values may cause a heat exchanger to be undersized when the heating load of a cold process stream suddenly rises due to an unexpected increase in cold stream heat capacity flow rate. This is apparent from the case study results of [52] in which the heat exchanger area at a particular location computed by considering only a single period operation (1.96 m^2) deviated by as much as 86 % from the maximum required heat exchanger area (14.44 m^2) obtained by considering a multi-period operation.

This discussion calls for a delicate treatment of parameter uncertainty in EISN optimization. Fig. 14 shows the four approaches by which parameter uncertainty has been incorporated in some EISN MP models. These methods include devising a stochastic programming model, formulating a multiperiod MP model, performing sensitivity analysis on the optimum EISN configuration, and allocating the costs or benefits of participating in an EISN by considering shutdown risks of participating entities.

Formulating a multiperiod optimization model is the most frequently used approach to account for uncertainty in EISN MP models. This method entails dividing a plant's operation into several time slices across which differences in the process parameter values are significant. The uncertain parameters in these models depend on the level of granularity required for the input parameters. For models requiring plant-level input parameters, such as [74,101], the uncertain parameters include the energy supplied and demanded by an entity. In Ref. [101], five plants were assumed to exchange waste heat with one other in which a portion of the waste heat was exported to two communities across four time slices. In each time slice, either the waste heat supply from a source plant or the waste heat demand from a sink plant or a community was deactivated. This caused the optimal values of the binary decision variables which indicate a connection between a source plant and a sink plant or community to change in each time slice. For instance, in time slice 1, plant D supplied waste heat to plant E which then supplied waste heat to community F; while in time slice 2, there was no connection between plants D and E and only plant D supplied waste heat to community F. Despite the thermodynamic soundness of the study results, the economic implications of underutilizing a pipeline during some time periods have not been addressed in this study. Alternatively, Asghari et al. [74] accounted for the variation in waste heat supply and demand across different time slices. To increase waste heat utilization, electricity production through mobile ORC systems was included as a waste heat use option on top of heat cascade. As compared to Ref. [101], this study offered more insights on how the optimization results could be practically implemented because it allowed investments for pipeline installation and for the deployment and relocation of mobile ORCs to be spread out across different time periods, subject to the allocated budget in each period.

Another multi-period MP model with plant-level input parameters is the one in Ref. [32]. In this study, only the heating demand of the adjacent residential areas had temporal variability across the four time slices. Then, the effect of varying the waste heat supplied or demanded by each plant to the optimum EISN configuration was investigated using sensitivity analysis as a post-optimization procedure. Just like in Ref. [101], the resulting optimum values of the binary decision variables which indicate a connection between a heat source and a heat sink varied in each time slice, but the economic implications of underutilizing waste heat transport pipelines during some time periods was not

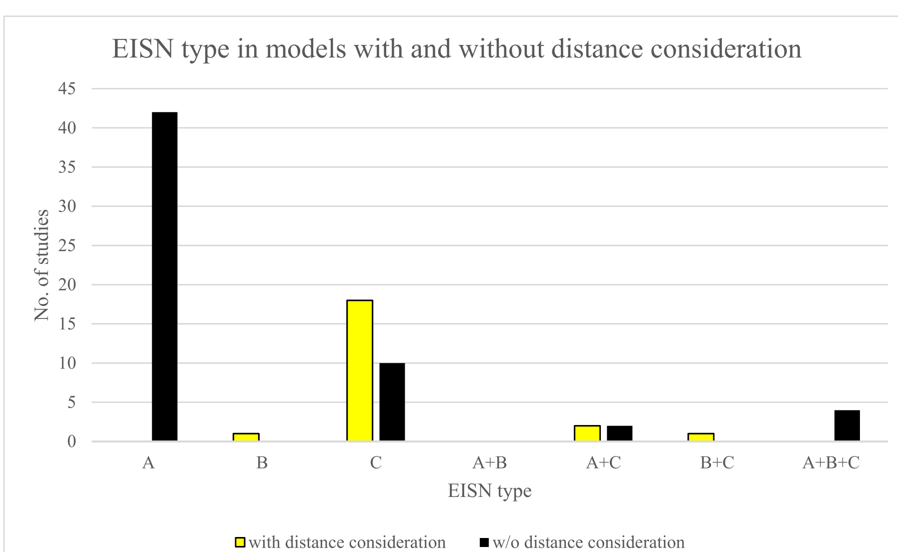

Fig. 10. Number of models for each EISN type that have and do not have consideration for the distance among integrated entities.

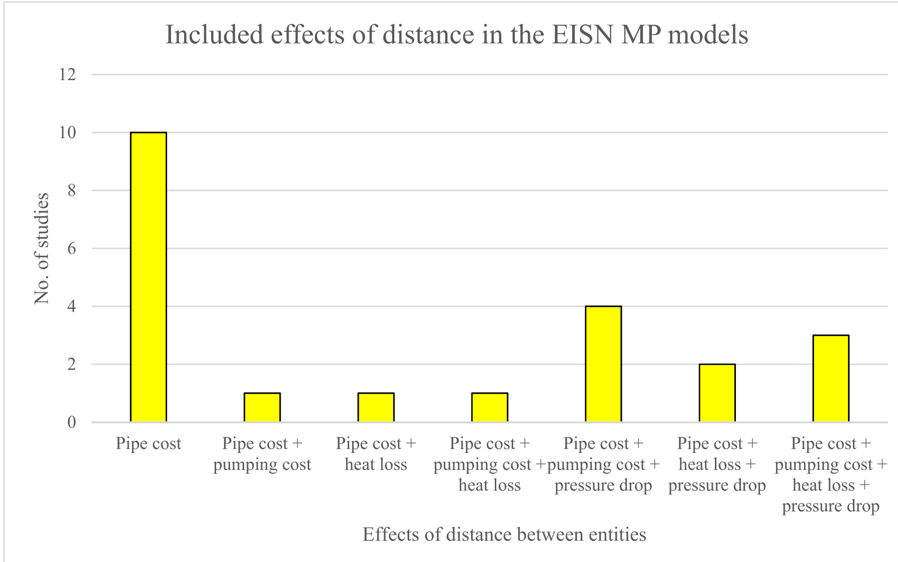

Fig. 11. Effects of distance incorporated in EISN MP models.

discussed.

The last multi-period MP model with plant-level input parameters is the one in Ref. [80]. Besides being a multi-period MP model, it is also a stochastic programming model which accounts for both the disruptions in waste heat supply and the temporal variations in waste heat demand. In this study, uncertainties were addressed by first transporting waste heat from the source plants to a TES. Then, stored heat from the TES was either used to drive an ORC or cascaded to sink plants. Finally, robust fuzzy chance-constraint programming was used to find the optimal solution by allowing certain energy balance constraints to be violated under a certain probability level.

Besides these four studies, multi-period EISN MP models with process-level input parameters also exist in the literature. Models of this kind attempt to solve two types of problem. First was determining the optimal heat integration in batch processing plants, which was addressed in Refs. [68,69,71,91,92], and [93] The second was optimizing a multi-period HEN configuration, which was tackled in Refs. [1,2,102,104,109,115,116], and [117]. But a multi-period MP model that addressed both problems also exists, which can be found in Ref. [94].

Heat integration in batch processing plants often incorporate TES in the MP model. This allows hot and cold process streams that do not exist at the same time to undergo indirect heat integration by enabling hot process streams to store heat in the TES and cold process streams to receive heat from the TES at different time periods. The most common decision variables in MP models that tackled this type of problem include the size of the TES tank and the temperature of the heat storage medium.

Conversely, as illustrated in Fig. 15, EISN MP models that optimized a multi-period HEN configuration set the optimal heat exchanger area for a particular location to be the maximum value of the heat exchanger area computed across all time periods for that location. In addition, these models also determined the minimum number of heat exchangers needed based on whether a pair of process streams has been connected in at least one of the time periods. That is, if the results showed that two process streams were matched in the first period but not in the second period, then these two process streams should still be matched in the optimum HEN configuration.

Several EISN MP models with plant-level input parameters, such as in Refs. [9,75], and [77] have been formulated as single-period optimization models in which the effect of parameter uncertainty was investigated through sensitivity analysis. In Ref. [9], only the heat demands of the sink plants were varied to determine any changes in the EISN costs. Alternatively, Afshari et al. [75,77] studied the effect of varying the amount of supplied and demanded waste heat, energy price, and carbon tax on the EISN costs through sensitivity analysis. Although these studies discussed the impacts of varying these parameters to the optimum EISN costs, how the optimum EISN configuration would change due to these parameter variations was not discussed. For instance, a pair of source plant and sink plant may be optimally matched at a certain energy price level, but when the price changes, the sensitivity results do not indicate whether the same pair of plants is still an optimal match.

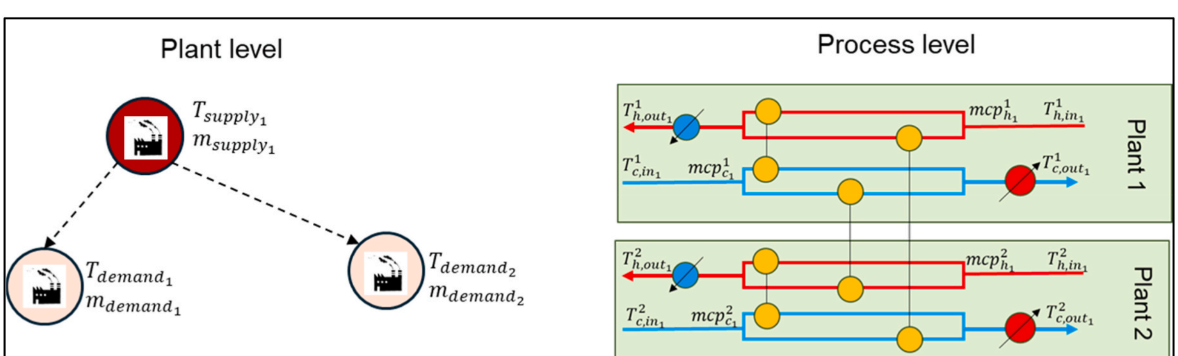

Fig. 12. Levels of technical detail for EISN MP model input parameters.

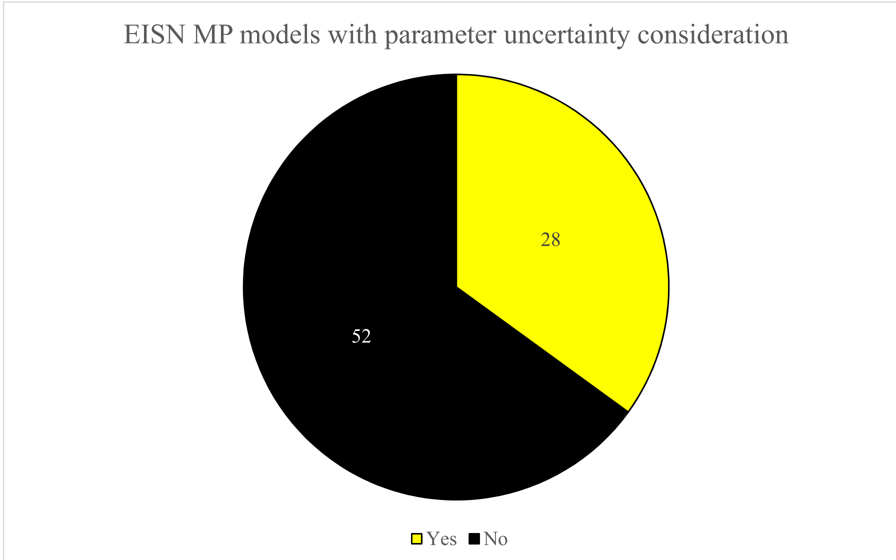

Fig. 13. EISN MP models with parameter uncertainty consideration.

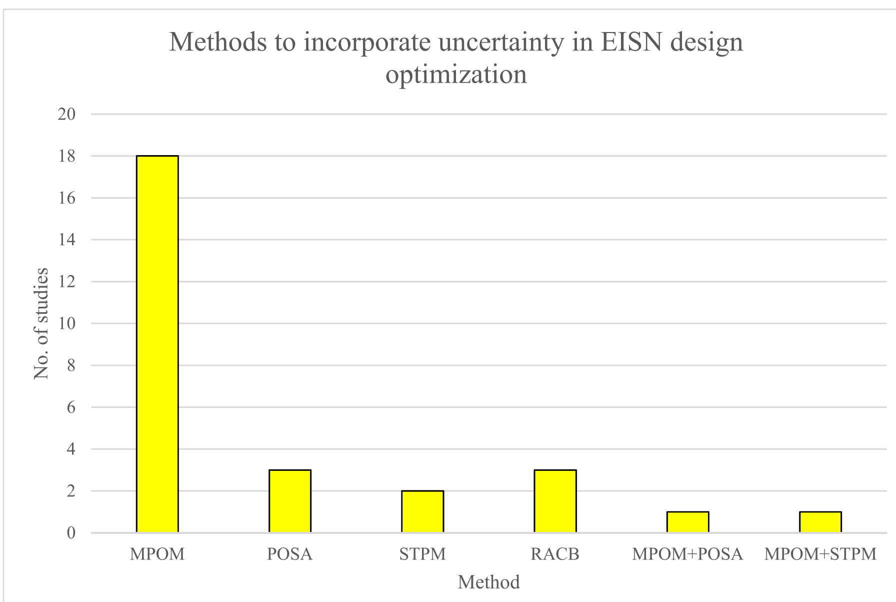

Fig. 14. Approaches to incorporate uncertainty in EISN design optimization. Legend: MPOM – multi-period optimization model; POSA – post-optimization sensitivity analysis; STPM – stochastic programming model; RACB – risk-based allocation of costs and benefits.

Besides these two approaches, the formulation of stochastic programming models to account for parameter uncertainty was explored in Refs. [76,99]. The MP models in both studies employed plant-level input parameters. In Ref. [76], the waste heat demand and supply were modeled as normal probability distributions, while the energy supply price and carbon tax were modeled as ranges of probable values. To address the computational complexity of optimizing a stochastic programming model, a sample average method was used. This approximation method involves taking different values of the uncertain parameters from their respective uncertainty sets to generate different scenarios. Then, the MILP model was solved for each scenario. The optimum objective function value corresponded to the average of the objective values computed from all scenarios. The problem with this approach is that the values of the binary decision variables indicating a match between the source plants and sink plants may also vary in each generated scenario. Thus, simply computing the average of the optimal objective function values in all scenarios may not be practically intuitive especially if each scenario results in a different optimum EISN configuration. Conversely, Thombre et al. [99] formulated a bilevel stochastic linear programming model to optimize a TES system between two batch processing plants. The uncertain parameters considered in the model were the quantities of heat supply and demand. However, the MP model proposed in this study can only be used in cases wherein two batch processing plants undergo indirect heat integration in which one of the plants serves as a heat source while the other serves as a heat sink.

Finally, there are also studies that considered heat supply and demand disruptions in allocating the costs or benefits of an EISN to the participating entities. These studies include [118,119], and [120]. In Ref. [118], a plant's expected losses due to the unforeseen shutdown of its collaborators are incorporated in the calculation of risk-based Shapley values for the optimal allocation of costs among the EISN participants. This cost allocation method was improved in Ref. [119] by considering how unplanned shutdowns in heat integrated plants could affect the heat exchanger areas for both intra-plant and inter-plant heat integration. Two HEN types were optimized in this study. The first sub-HEN was for the normal condition, in which the plants operated under design conditions, while the second sub-HEN was for the abnormal condition, in which one of the plants encountered an unforeseen shutdown. Since plant shutdowns would result to the underutilization of inter-plant heat exchangers, the second sub-HEN was only composed of the intra-plant heat exchangers. To compensate for the lack of heat transport in the inter-plant heat exchangers, the intra-plant heat exchanger areas in the second sub-HEN were higher than those in the first sub-HEN. Finally, the maximum intra-plant and inter-plant heat exchanger areas that were computed in each condition were used for the capital cost computation and were considered as the final heat exchanger areas in the optimum HEN configuration. The total HEN cost was then allocated to the integrated plants using the methodology proposed in Ref. [118]. Finally [120], modified the cost allocation method proposed in Ref. [118] by basing the optimal profit allocation on risk-based Owen values, instead of Shapley values. The advantage of using Owen values is that it considers the contribution of entities that have a natural tendency to form a sub-coalition in the total profit of a grand coalition. This tendency is not captured in Shapley value calculation because the profit allocation using Shapley values is only based on a plant's marginal contribution to the grand coalition. Another modification that Tian and Li [120] made on the approach proposed in Ref. [118] was that instead of calculating the profit allocation after the HEN optimization step, the Owen value was embedded in the optimization model itself as one of the decision variables. However, since the Owen value can only be determined after the computing total HEN cost, the MINLP model was then solved using a bilevel optimization approach. However, this study based the profit of each plant on the difference between the costs of participating in a multi-plant direct heat integration and of implementing intra-plant heat integration only. The problem with this approach is that intra-plant heat integration is an energy efficiency initiative that plants would naturally implement on their own before they even consider participating in a multi-plant HEN. Therefore, the computation of a plant's profit should have been based on the avoided costs due to its participation in multi-plant heat integration (i.e., reduced utility costs, reduced carbon taxes, etc.)

4. Discussion on potential research directions

The discussion on Section 3.1 has shed light on how the total annualized cost has been overly prioritized as an optimization objective in most EISN MP models. Although prospective EISN participants, especially of Type "C" EISNs, intuitively desire to keep the expenditures for establishing and operating an EISN to a minimum, simply determining the EISN configuration with the lowest overall cost is not enough for stakeholders to decide whether participating in an EISN would be economically viable for them. The logical question that potential EISN participants would ask after knowing the total EISN cost is how the overall cost and the resulting benefit/s should be fairly divided among

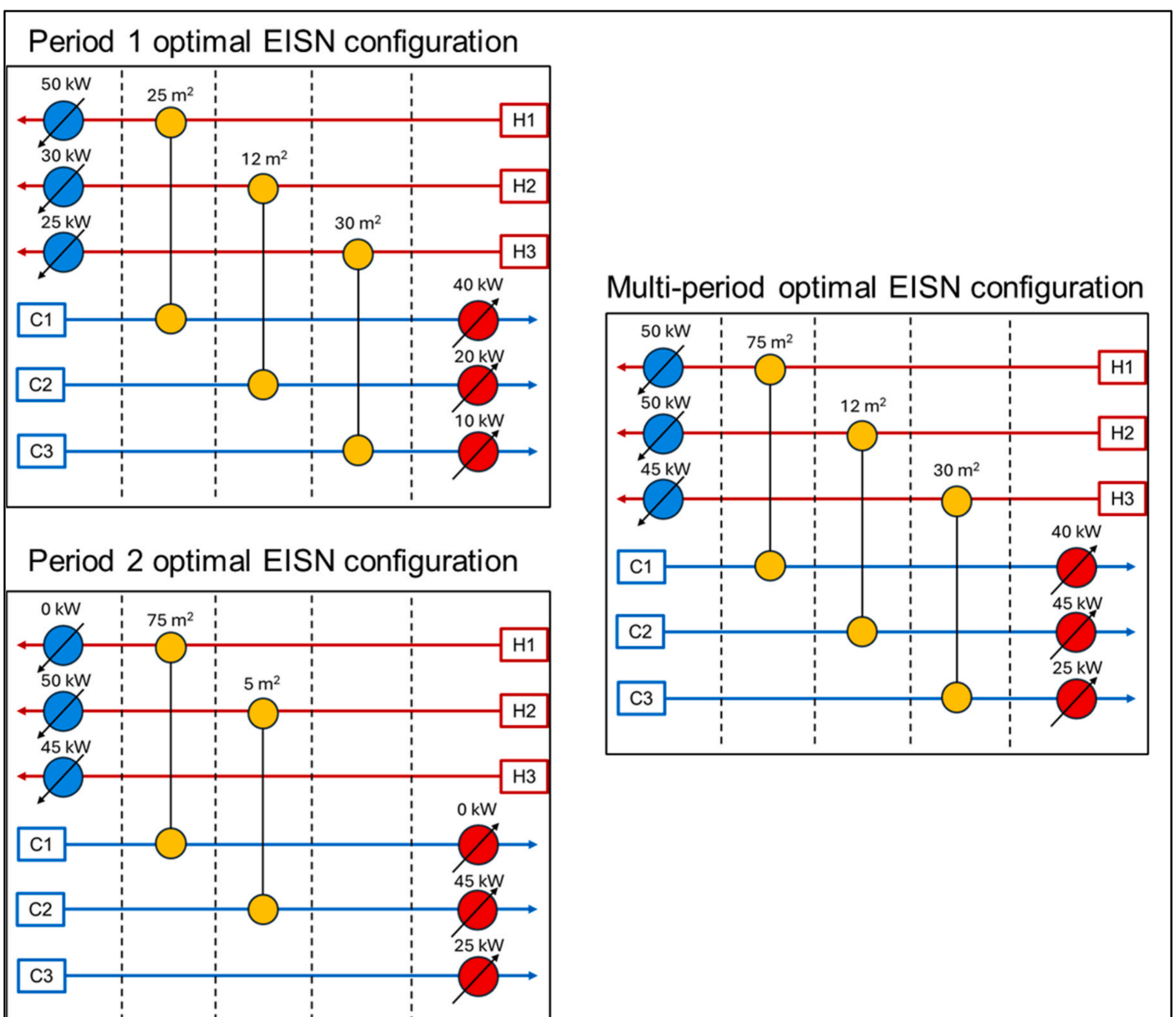

Fig. 15. Approach employed in multi-period optimization models to determine the optimal EISN configuration.

the participating entities. Although the issue of equitable cost and benefit allocation can be addressed by game theoretic concepts, most models can only determine the allocation for each entity as a post-optimization step, while for others, only either the apportioned cost or profit can be determined from the optimization results. In this regard, future studies can formulate novel optimization objective functions which reflect the costs that each participant must shoulder to establish and operate the EISN, and at the same time, the benefits that each participant can derive from the EISN.

Another potential research area on EISN MP model objective functions is to determine and incorporate the most relevant environmental and social impacts of establishing an EISN in the MP model. As discussed in Section 3.1, most existing EISN models only focus on the minimization of the total EISN costs. However, ensuring the overall sustainability of an EISN entails the consideration of its environmental and social aspects. In this regard, formulating a multi-objective MP model which involve assigning different prioritization weights to the different objective functions may not be practical due to the hyper-dimensionality of the resulting Pareto curve, especially if more than three objectives are considered. In addition, doing so involves making compromises among the three sustainability dimensions. This tradeoff concept, which underpins the relative sustainability paradigm, is quite contentious because it considers the three sustainability dimensions to be of equal importance. To address this, hard constraints on the maximum allowable adverse environmental and social impacts of an EISN could be formulated instead. Employing this approach can guarantee that the resulting optimum EISN configuration would function within the appropriate operating space of the various planetary boundaries, a concept which is aligned with the absolute sustainability paradigm [121]. However, the downside of this approach is determining how to equitably downscale the maximum allowable threshold values of all planetary boundaries from a global scale down to a national scale, and from a national scale down to a specific economic sector in a certain locality. Resolving this matter is one of the most crucial issues that hinder the more widespread adoption of the absolute sustainability viewpoint in global and national environmental policies, more so in energy systems and EISN MP modelling.

In addition, achieving energy efficiency through industrial waste heat recovery leads to a non-trivial problem on optimal resource allocation, in which waste heat serves as the shared resource. As discussed in Section 3.2, most MP models considered the cascading of waste heat from a heat source to a heat sink as the only waste heat use option. Although there are studies that considered other ways to utilize waste heat, such as allowing it to drive an ORC for electricity production or an ARS for cooling energy production and even upgrading it to a higher temperature heat stream, MP models that simultaneously consider multiple utilization pathways are still scarce. Limiting the waste heat use options to only a few choices could lead to a sub-optimal utilization of this shared resource. Therefore, potential studies could focus on analyzing the trade-off among the various waste heat utilization pathways to determine the best use case for waste heat. Doing so could enhance the economic viability of establishing an EISN.

In relation to the foregoing, one of the probable reasons as to why most studies only consider simple waste heat cascade is that different types of entities (i.e., non-industrial areas) which require other forms of energy are often not integrated within the EISN model. In this regard, by including the different energy needs (i.e., electricity, cooling energy) of various entities, other waste heat use options could then be explored.

However, increasing the number of integrated entities, along with the number of waste heat utilization pathways, comes at the expense of increasing the model complexity, especially when employing a simultaneous approach for EISN optimization like the one proposed by Yee et al. in Refs. [45,46], and [47]. Employing a simultaneous approach is attractive because it can determine the optimal tradeoff between utility costs and capital costs for establishing an EISN [118]. However, its biggest downside is that it involves solving an NP-hard non-convex MINLP model which has a computational complexity of exponential time $O(2^n)$, where n is the number of bits needed to represent the model [122]. One model feature which contributes to the problem's complexity is the presence of binary decision variables whose optimal values are typically determined through the branch-and-bound algorithm. This algorithm involves maintaining a tree of feasible solutions for the linear relaxations of the integer program. Thus, the higher the number of binary decision variables in an MP, the higher would be the number of branches corresponding to the linear relaxation sub-problems of the original integer program from which the optimal feasible solution would be obtained. In addition, MINLP models involving indirect heat integration contain bilinear terms due to the product of the heat capacity flow rate and temperature of the intermediate heat transfer fluid in the energy balance constraints. This is a source of nonlinearity which increases the model's complexity. Finally, another reason why solving an MINLP-based EISN optimization problem is difficult is due to the presence of non-convex terms in the computation of the log mean temperature difference (LMTD) for heat exchanger area calculations. As seen in Equation (1), numerical difficulties are encountered in LMTD computation when the temperature differences between the hot and cold streams at the left and right sides of a heat exchanger (θ_1 and θ_2 respectively) are equal [46].

$$LMTD = \frac{\theta_1 - \theta_2}{\ln \frac{\theta_1}{\theta_2}} \tag{1}$$

To circumvent this difficulty, most models use Chen's approximation for LMTD calculation. This approximation method has the advantage of resulting to a zero LMTD value when either θ_1 or θ_2 is zero. However, it yields to a non-convex LMTD equality constraint due to the presence of fractional powers of θ_1 and θ_2, as seen in Equation (2).

$$LMTD = \left(\theta_1 \bullet \theta_2 \bullet \frac{\theta_1 + \theta_2}{2}\right)^{\frac{1}{3}} \tag{2}$$

The above discussion shows that solving a large-scale MINLP model involving multiple waste heat use options and integrating different entity types is computationally difficult. Thus, future studies could focus on developing novel approaches to simplify existing EISN MP models so that near-optimal solutions could be obtained in a reasonable amount of time. For instance, by combining the use of McCormick envelopes [123] to generate convex under-estimators for the bilinear functions and of the Lambert W-function [124] to provide an explicit solution to the LMTD, the two sources of nonconvexities in MINLP-based EISN models could be addressed.

Furthermore, future studies could also focus on formulating MP models which reflect the actual layout of the entities to be integrated. As discussed in Section 3.4, despite how intuitive distance consideration should be in EISN modelling, most models do not incorporate this factor. Including this aspect in EISN models could ensure that the economic and thermodynamic impacts of integrating entities are accounted for. The economic implications include piping and pumping costs, while the thermodynamic implications include pipeline heat losses and pressure drops. Considering these impacts adds another set of feasibility constraints to ascertain whether two entities should indeed be connected under optimum conditions.

Another potential research direction is determining the best approach to incorporate parameter uncertainty in the MP model. This can ensure the robustness of the resulting EISN configuration and increase the stakeholders' confidence in participating in an EISN. Addressing this matter is crucial since it can affect the choice of waste heat utilization equipment in the optimum EISN configuration. To demonstrate how parameter uncertainty can affect the capacities and types of equipment to be included the optimal EISN configuration, consider a multi-period optimization model which allows multiple waste heat use options and incorporates both the variability in process parameters and the risks of unforeseen plant shutdowns in the indirect heat integration of two plants. In the first time slice, plants A and B are operating under normal conditions, and the results show that the optimal use for the waste heat coming from a hot process stream in Plant A is to simply cascade it to a cold process stream in Plant B. However, in the second time slice, plant B suddenly shuts down, and the results reveal that the optimal use for the waste heat from plant A is to let it drive an ORC to generate electricity. Finally, in the third time slice, plants A and B are both operational but based on the results, only a portion of the waste heat coming from plant A must be transferred to plant B, while the rest is used to drive an ORC. In such a case, determining the optimal heat exchanger areas for waste heat cascade and the optimal size of the ORC plant becomes non-trivial because tradeoffs must be made between maximizing waste heat recovery and maximizing the usage of waste heat utilization equipment. One way to address this is to investigate the implications on the resulting optimal objective function value of sizing the heat exchangers and ORC plants based on either their average loads or maximum possible loads. However, formulating either a stochastic or a multi-period MP model to account for parameter uncertainty can exponentially increase the computational difficulty of solving a comprehensive EISN MP model, especially one that employs a simultaneous approach. This modelling challenge is illustrated in Fig. 16.

Since industrial energy management starts with setting targets for energy use and greenhouse gas emissions reduction, future models can therefore include hard constraints in which prospective EISN participants can set their respective maximum external utility consumption targets for their processes. By doing so, industries can be guaranteed that the resulting EISN configuration would allow them to fulfill their energy efficiency targets. Incorporating such hard constraints can be considered as a proactive modelling approach to designing EISNs because this would allow industries to directly influence the EISN optimization results according to their energy policies. Furthermore, these models could also be extended to reflect how the optimal EISN configuration would evolve as the participating entities increase their energy efficiency targets over time.

As a final note, the insights that can be derived from this research are somehow limited by the scope of its analysis. First, since only MP models with waste heat recovery are considered in this study, the effect of recovering other forms of excess energy, such as pressure energy, in the formulation of EISN MP models is not investigated. Considering excess pressure energy would have had implications on how the effect of inter-entity distance is represented in an EISN MP model. Second, this work has also not investigated how complementing waste heat recovery with energy recovery from industrial waste incineration would affect the formulation of EISN MP models. Examining such models could have complemented the dearth of Type B + C EISN models that have been considered in this study. Finally, MP models that optimize the configuration of an industrial symbiosis network with both excess heat and material waste recovery and reuse are also not considered in this study. Investigating the formulation of such models could have increased the practicality of the results from the optimization of an industrial symbiosis network since, in practice, material-based symbiosis is the less complicated form of industrial symbiosis to establish compared to energy-based symbiosis.

5. Conclusion

This study has comprehensively analyzed the existing MP models for EISN optimization based on five key features: the entities integrated in the EISN, the types of objective functions in the models, the utilization pathways for the recovered waste heat, the effect of including the distance between process streams or plants, and the approach to incorporate parameter uncertainty. By investigating the existing models based on these features, several gaps in EISN MP modelling have been uncovered.

1. Formulating economic objective functions which reflect how participating entities can fairly allocate the costs and benefits of establishing an EISN could allow these potential stakeholders to decide if joining in such collaborative energy efficiency initiative would be economically sound for their respective enterprises.
2. Ascertaining the most relevant environmental and social impacts to incorporate in an EISN MP model could ensure the overall sustainability of EISN design.
3. Analyzing the tradeoffs among the various waste heat utilization pathways to determine the best use case for waste heat could enhance the economic feasibility of establishing an EISN.
4. Integrating other types of entities in the EISN, besides the plants themselves, could enhance waste heat recovery, but it would likely increase the model complexity. Therefore, novel approaches to simplify the existing MP models must be developed to find near-optimal EISN configurations in a reasonable amount of time.
5. Future MP models could incorporate the thermodynamic and economic implications of incorporating the physical layout of integrated entities on the optimum EISN configuration.
6. Determining the most appropriate approach to incorporate parameter uncertainty in the model could ensure the robustness of the optimum EISN configuration and increase the confidence of prospective stakeholders in participating in an EISN.
7. Setting hard constraints on the maximum external utility consumption could ensure that the individual energy efficiency targets of the participating entities would be achieved through the resulting optimum EISN configuration.

Improving the formulation of existing EISN MP models by addressing these gaps could enhance the model's representation of actual conditions and increase the overall sustainability and viability of the optimal EISN configuration. This could lead to the formulation of more comprehensive EISN MP models that can be used as a tool for designing eco-industrial parks by pertinent government institutions or private industrial estate developers.

To enhance the practicability of the insights that can be derived from this study and from future industrial symbiosis research, addressing the limitations mentioned in Section 4 is recommended. These include the limited forms of excess energy recovery included in EISN MP models, the sparsity of analysis on Type B + C EISN MP models in which waste heat recovery is complemented by energy recovery from industrial waste incineration, and the non-consideration of both material-based and

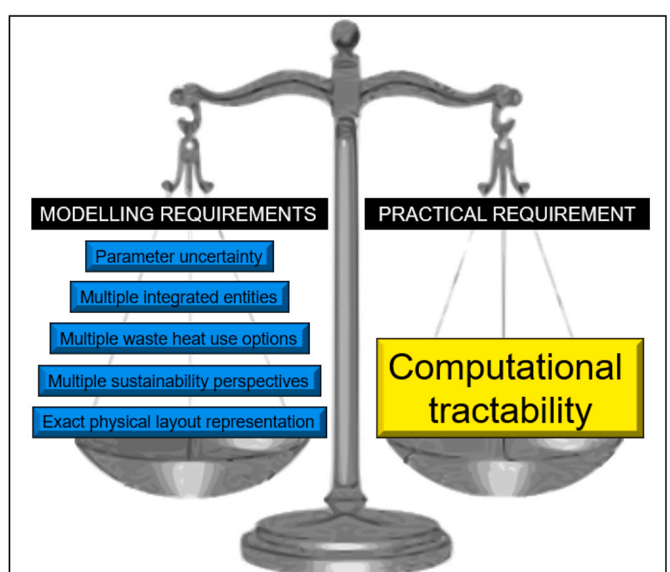

Fig. 16. Conundrum of formulating a comprehensive EISN MP model.

energy-based symbiosis in the analysis and formulation of MP models. These preclude the creation of more comprehensive MP models for optimizing the configuration of an industrial symbiosis network consisting of all possible synergistic exchanges among participating entities.

CRediT authorship contribution statement

La Verne Ramir D.T. Certeza: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft. **Aloisius Rabata Purnama:** Writing – review & editing, Supervision. **Aniq Ahsan:** Writing – review & editing, Supervision. **Jonathan S.C. Low:** Writing – review & editing, Supervision, Funding acquisition. **Wen F. Lu:** Writing – review & editing, Supervision.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used Rayyan.ai [125] to document the entire systematic literature review process, starting from the collation of studies up to the screening of articles according to various eligibility criteria. After using this service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:La Verne Ramir Dela Torre Certeza reports financial support was provided by Singapore Institute of Manufacturing Technology. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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