Simulation Based Electricity Demand Response Considering Product Sequence and Onsite Renewable Energy

BY

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THESIS

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NOMENCLATURE

$E_{total}(t)$	Total demand energy in time step t in kWh
$E_{PV}(t)$	Energy generated by the PV source in time step t in kWh
$E_{wind}(t)$	Energy generated by the wind turbines in time step t in kWh
$E_{bat}(t)$	Battery state of charge in time step t in kWh
$E_{net}(t)$	Energy supplied by the grid in time step t in kWh
$E_{spl}(t)$	Energy sold to the grid in time step t in kWh
R_{W_OFP}	Electricity consumption rate in winter during the off peak period in ($/kWh)
R_{W_ONP}	Electricity consumption rate in winter during the on peak period in ($/kWh)
R_{S_OFP}	Electricity consumption rate in summer during the off peak period in ($/kWh)
R_{S_ONP}	Electricity consumption rate in summer during the on peak period in ($/kWh)
R_{spl}	Rate at which the surplus electricity can be sold back to the grid in ($/kWh)
R_{bat}	Battery initial investment including replacement ($/kWh)
R_{W_DC}	Demand charge in winter in ($/kW)
R_{S_DC}	Demand charge in summer in ($/kW)
F_{max1}	Maximum charge rate in %/h
F_{max2}	Maximum discharge rate in %/h
C_{min}	Minimum battery state of charge in %
C_{bat}	Battery storage in kWh

η_{BD}	Discharge efficiency of battery bank
η_{BC}	Charge efficiency of battery bank
η_{AD}	AC-DC conversion efficiency of the invertor
η_{DA}	DC-AC conversion efficiency of the invertor
CRF	Capital recovery factor
d	Discount rate (%)
A	Analysis period

LIST OF ABBREVIATIONS

RET	Renewable Energy Technologies
LCOE	Levelized Cost of Energy
GHG	Greenhouse Gases
TOU	Time of Use
DES	Discrete Event Simulation
SBO	Simulation based Optimization
PV	Photovoltaic
DG	Distributed Generation
SOC	State of Charge
GHI	Global Horizontal Irradiance
O&M	Operation and Maintenance

SUMMARY

The growing electricity demand during peak demand periods has resulted in the need to build and develop additional infrastructure. Moreover, the rise in fuel prices have opened up opportunities to investigate renewable energy technologies (RET) to meet this growing demand. Greenhouse gas (GHG) emissions can be reduced and significant savings can be achieved on electricity bills and carbon credits. Compared to the existing literature on energy load management, very few studies integrating electricity demand response programs and renewable energy have been conducted.

In this thesis, initially, we develop a discrete event simulation (DES) model considering a manufacturing facility with multiple stations and multiple product types. The production schedule is determined by optimizing the product sequence and labor requirement under the constraint of production throughput using simulation based optimization (SBO). Later, we establish an agent based simulation model considering a renewable Distributed Generation (DG) system and a Time of use (TOU) electricity pricing program to minimize the electricity cost incurred from the grid. The DG system features on-site generation from RET and a battery storage. The dispatch strategy of the DG system is based on the on-peak and off-peak periods of the day, availability of renewable energy, energy demand, and battery state of charge. Also, the size of battery storage is determined using SBO for specified capacities of RET. The capacities of the DG system are chosen from the annual savings plot. Two case studies considering a PV-battery hybrid system and a PV-wind-battery hybrid system are compared with the baseline scenario to illustrate the effectiveness of the proposed model.

1 INTRODUCTION

The industrial sector is the largest consumer of energy and accounts for 31% of total energy consumption in the United States as shown in Figure 1 [1]. Over the past twenty years, energy prices are rising steadily and forecasts show an increasing trend due to infrastructure upgrades, increase in fossil fuel prices and climate change legislation [2]. The manufacturing sector consumes a large amount of electric energy for process heating, machine drive, heating, ventilation and air conditioning, and other areas in the manufacturing facility [1].

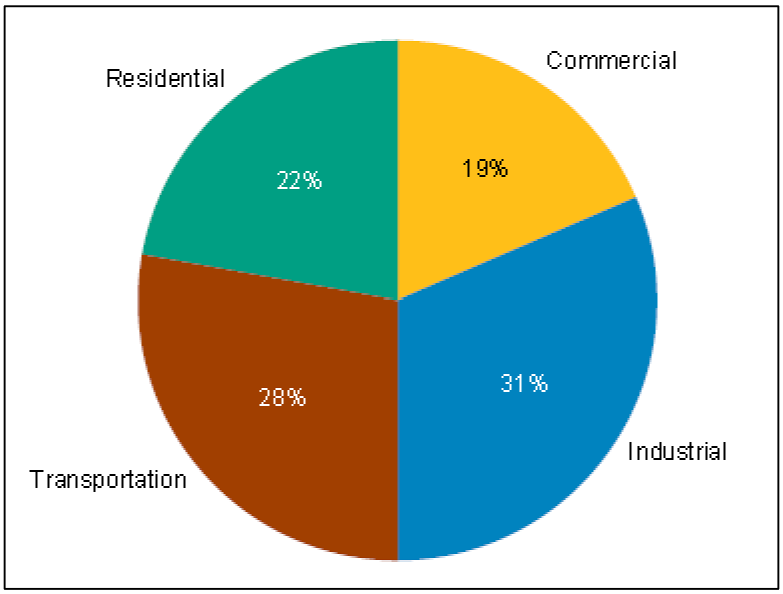

Figure 1. End use sector share of Total consumption (2011)

(Source: Energy Information Administration. Annual Energy Review 2011)

Increasing electricity demand has given rise for more electricity generation and distribution equipment since it is a form of energy that needs to be generated, distributed and consumed immediately. It is estimated that about \$1.5 trillion to \$2 trillion investments for new generation capacities, transmission, and distribution will be required to meet the growing demand by 2030 [3]. Another potential concern with the growing demand is the emission of Greenhouse Gases (GHG). Electricity generation is the largest source of GHG emissions in the United States. GHG emissions are the leading cause of global warming and climate change and are a threat to the sustainability of the ecosystem [4].

In order to curb the potential negative impacts of the rising demand, one approach initiated from the supply side is the demand response program. The Federal Energy Regulatory Commission (FERC) [5] defines demand response as:

"*Changes in electric usage by demand-side resources from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized.*"

Energy efficiency and demand response are identified as closely related concepts giving customers a perspective for their application. While information on various demand response programs is readily available to customers, the opportunity to target loads that can be easily shifted or curtailed in return for reduced electricity prices and other financial benefits has become evident [6]. The various types of demand response programs are categorized in two major types, i.e. price based and incentive based. In price based programs, electricity prices vary based on the time of the day with the price being the highest during on-peak hours. These programs encourage customers to shift their load to off-peak hours. In incentive based programs, the customer agrees to curtail their load with a prior notice issued by the utility company in exchange for reduced electricity prices. The notification for load curtailment can be issued on short notice and the customer has to bear the consequences or develop load management strategies to avoid any loses [6]. Many studies focusing on time based demand response programs for production scheduling in manufacturing facilities have been conducted. For example, Ashok designed an optimal production schedule using TOU tariff system and achieved significant cost savings for a steel plant [7]. Wang and Li used TOU based demand response to minimize the electricity cost under the constraint of production throughput for sustainable manufacturing systems [8]. Bego et al. formulated a problem to identify the reservation capacity and minimize the overall production cost [9]. Dababneh et al proposed a peak load reduction model for combined manufacturing and HVAC systems considering heat generated by the production equipment under the constraint of production throughout. [10]

In addition to demand response programs, many studies focusing on on-site generation technology facilitating manufacturers' independence from the power utility company have been implemented. Renewable hybrid energy systems can significantly contribute to cost reduction by minimizing the capital investment of new generation capacities, transmission and distribution; moreover, solar and wind are clean energy sources that do not emit GHGs and contribute to sustainable development. Levelized cost of electricity (LCOE) is a term used to compare the economic effectiveness between the electricity generated by the renewable systems and the other conventional forms of electricity [11]. It is also referred to as the cost at which energy must be sold to breakeven over the lifetime of the technology [12]. The LCOE of the popular renewable energy technologies (i.e. solar and wind) are continually dropping. The LCOE comparison of solar and wind along with natural gas is shown in Figure 2 and Figure 3[11].

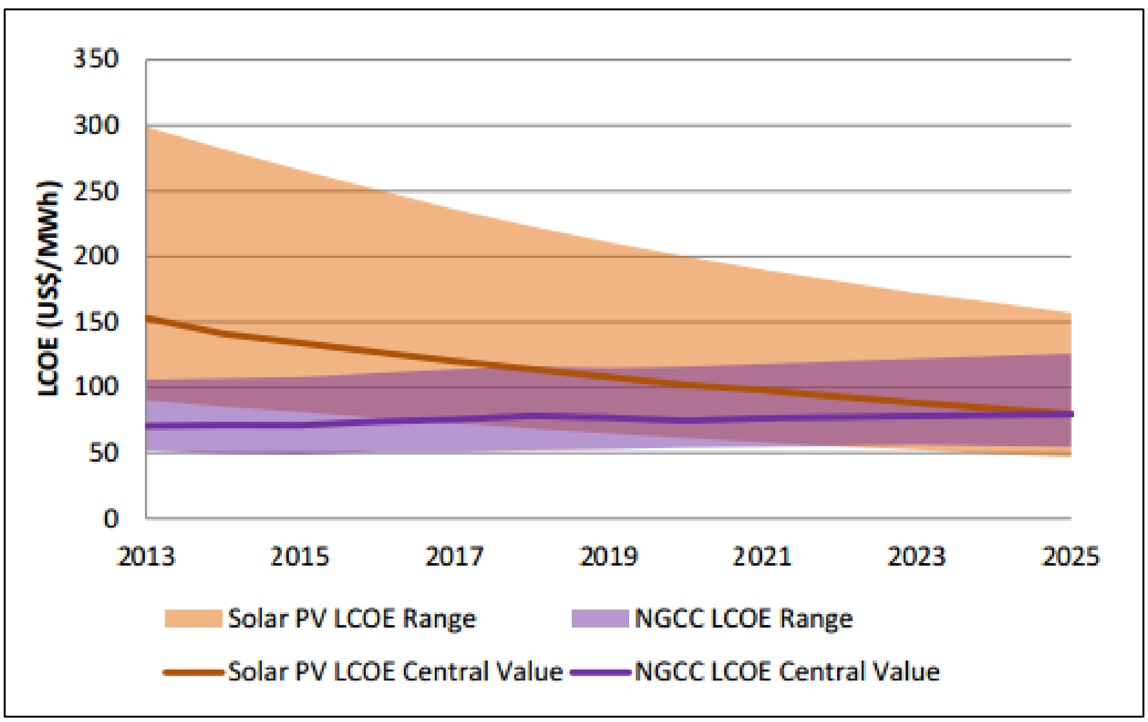

Figure 2. United States utility-scale solar PV LCOE compared to NGCC

(Source: http://www.nrel.gov/docs/fy15osti/63604.pdf)

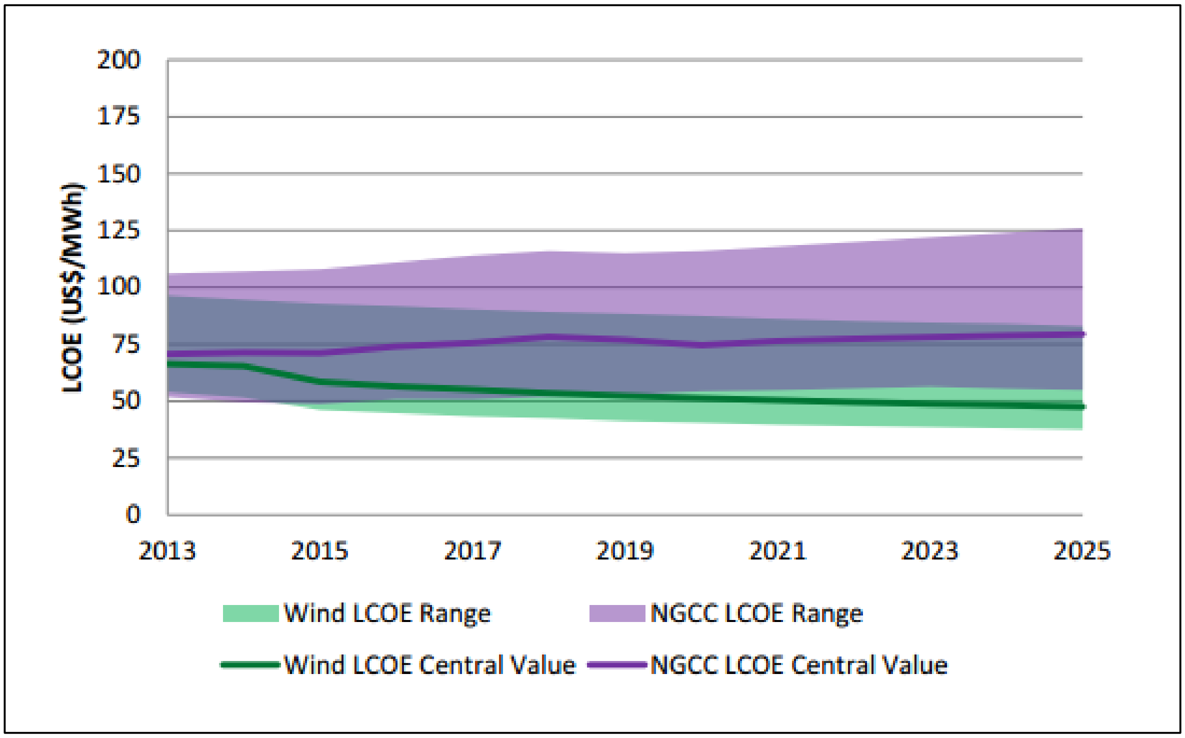

Figure 3. United States utility-scale wind LCOE compared to NGCC

(Source: http://www.nrel.gov/docs/fy15osti/63604.pdf)

Technically, RET can replace conventional units. Moreover, they can reduce dependence on fuel from foreign countries and gain environmental benefits from low GHGs emission [13]. Various studies focusing on sizing and control for standalone renewable hybrid energy systems like PV-wind-battery hybrid power system, PV-wind-diesel hybrid system, PV-diesel-battery hybrid system and many more have been reported [14-22].

In the past decade, smart-grid technology has made the integration of RET with the grid possible [23]. This has led to building a more reliable hybrid power system by eliminating power losses due to the stochastic nature of solar and wind energy sources. Many studies have focused on determining the optimal capacities of renewable energy technologies that are integrated with the microgrid. For example, Taboada et al. formulated a stochastic decision making model to optimize the capacity of a solar photovoltaic based co-generation system for semiconductor wafer fab production [24]. Villarreal et al. proposed a mathematical model for a grid tied PV-wind hybrid system and achieved significant cost savings for wind turbines in the semiconductor industry [25]. Some studies have also focused on the evaluation and cost effectiveness of battery systems in grid tied hybrid system. For example, Hittinger et al. used Energy System Model to evaluate the performance of the Aqueous Hydroid Ion (AHI) battery and lead acid battery with PV system while connected to the microgrid [26]. Ciez and Whitacre implemented a time-step battery degradation model that considers battery type, SOC, number of battery replacements, renewable energy and discount rate to determine the lowest LCOE [27]. None of the literature mentioned above considered demand response programs in their studies. More recently, Santana-Viera et al. implemented an incentive based interruptible/curtailment demand response program with an on-site PV-wind generation hybrid system for a large manufacturing facility and aimed to determine the optimal capacities of PV and wind turbines that can maximize the annual savings [28]. This work does not consider battery, which is an important mechanism to balance energy generated by PV and wind turbines.

Accordingly, in this thesis, first, a discrete event simulation model to determine the optimal production schedule based on optimizing the product sequence and labor requirement is built. Then, an agent based model under a TOU electricity tariff program with on-site renewable energy technology and a battery bank is developed while minimizing the overall cost of manufacturing. SAM (System Advisor Model) is used to model the PV system and wind turbines to obtain the energy generated by each system for their respective capacities. The hourly demand obtained from the discrete event model in AnyLogic and hourly power generated by the PV system and wind turbines (data obtained from SAM) serve as inputs to AnyLogic's agent based model. The optimization experiment built in the agent based model is used to obtain the optimal battery bank storage considering the overall cost of manufacturing (see Chapter 2 for details). To illustrate the effectiveness of the proposed model, we run three cases, i.e. the baseline scenario, a PV-battery hybrid system, and a PV-wind-battery hybrid system (see in Chapter 3 for details). Moreover, a sensitivity analysis is conducted considering variable weather and economic data (see Chapter 4 for details). Finally, the conclusions and future work are discussed in Chapter 5.

2 METHODOLOGY AND MODEL BUILDING

2.1 Methodology

The goal of this study is to find the optimal product sequence and labor requirement for a paint shop, and to determine the capacities of renewable DG units under the TOU demand response program to minimize cost incurred from the grid. The paint shop manufacturing system considered consists of a single production line used to produce various types of products. In order to achieve the aforementioned objective, the methodology is divided into two parts. In the first part, a discrete event simulation model in AnyLogic is built to decide on the product sequence and the labor assignment for each operation. In the simulation model, the labor assignments and the product sequence are determined while minimizing the completion time under the constraints of demand and total labor limit. Finally, we obtain an optimal production schedule for further study. In the second part, we build an agent based model in AnyLogic considering the on-site generation from renewable DG system under the TOU demand response program. The hourly generation of the renewable energy technologies is modeled in SAM. The discrete event and agent based models are built using AnyLogic 7 Personal Learning Edition 7.2.0. Figure 4 summarizes the integration of the three models.

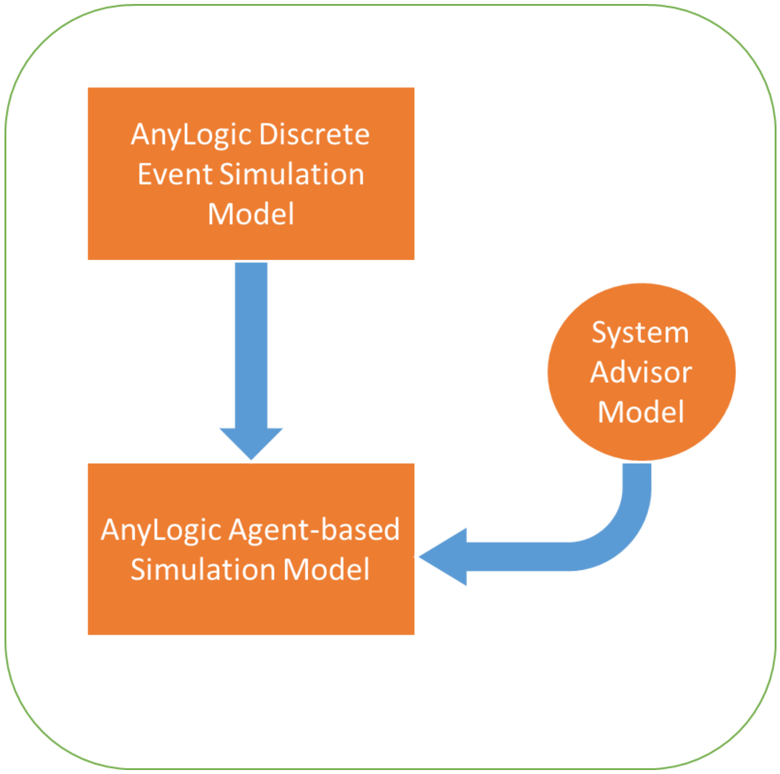

Figure 4. Integration of three models

2.2 Discrete Event Model

The discrete event model represents the system as a sequence of operations performed on entities [29], in this case the entities are the parts in the production line. The objects used in the simulation model are source, queues, seize-delay-release blocks, services, resource pools, restricted areas, select-output, and sink. The parts arriving at the source are queued according to their respective priorities. The seize-delay-release blocks are used to seize machines, while service blocks are used to seize operators/painters, process the parts and release them. Figure 5 shows a snapshot of the DES model in AnyLogic.

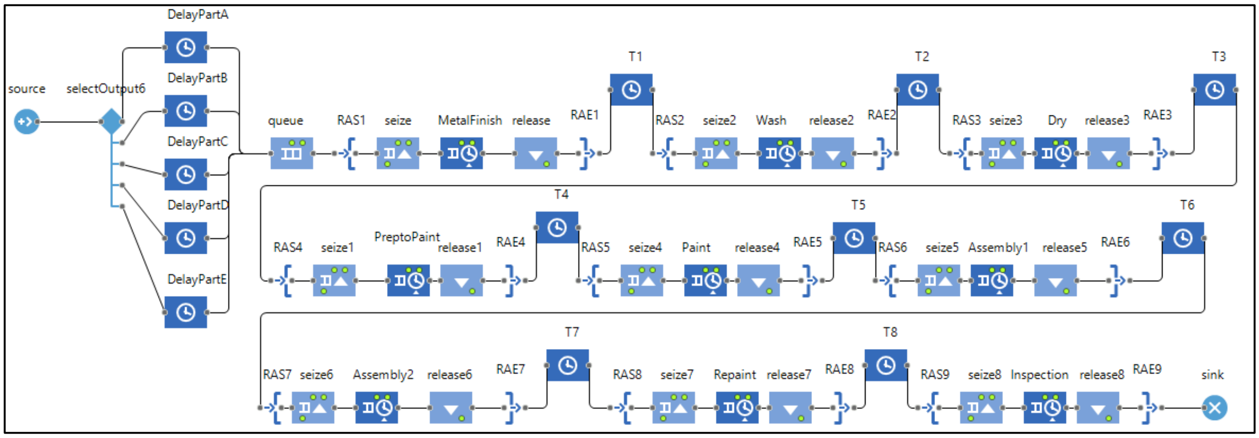

Figure 5. Discrete event model in AnyLogic

T1 through *T8* are the delay blocks in the model and represent the transportation time of the parts between the stations. *RAS1* through *RAS9* and *RAE1* through *RAE9* represent the restricted areas for the parts since only one part can be processed at the station at any given time. The information on cycle time and labor requirement for different products is imported into the AnyLogic database. Database is an element in AnyLogic used to read data from an imported spreadsheet and incorporates it in the simulation model. To define a trait for each product type, the parts being produced are created by defining a custom agent type having parameters ‘products’ of type ‘string’, ‘number’ of type ‘integer’, ‘arrivals’ of type ‘integer’ and ‘priority’ of type ‘integer’. Each operation, depending on the product type, takes a value for the cycle time and seizes the labor based on the information in the database. For each new agent entering the service module, for example ‘Metal-Finish’, the block will search the specified column in the database for the record that has the value in the ‘products’ column equal to the name of the agent currently being processed by the block. The database SQL query is shown in Figure 6. The MTBF and MTTR information about the machines inputted into the resource pool objects is shown in Figure 7. In order to count the parts disposed at the sink object, five variables representing the product types are created and Figure 8 shows the code to count finished parts based on product type.

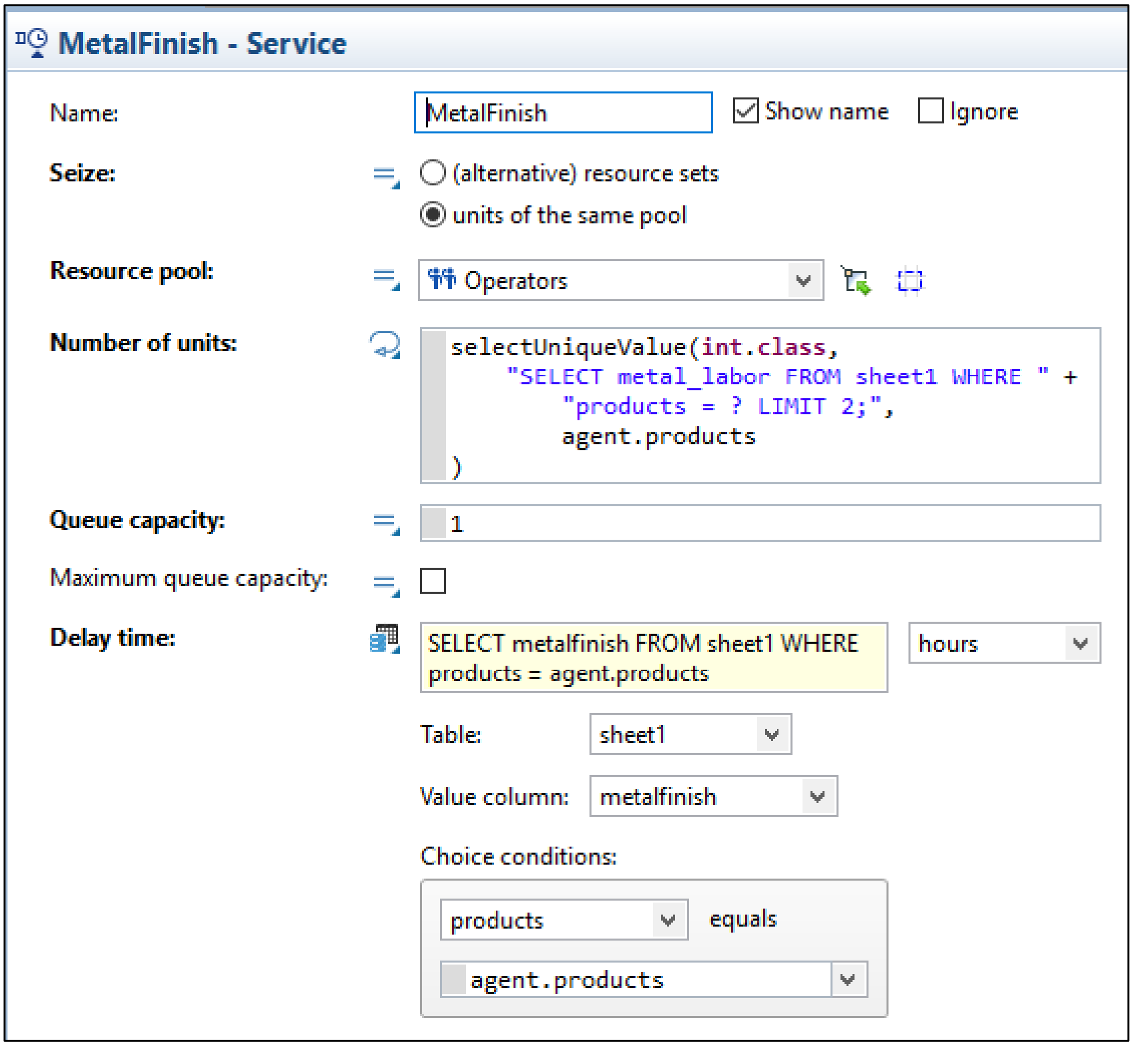

Figure 6. SQL query to retrieve labor information from the database for a given operation

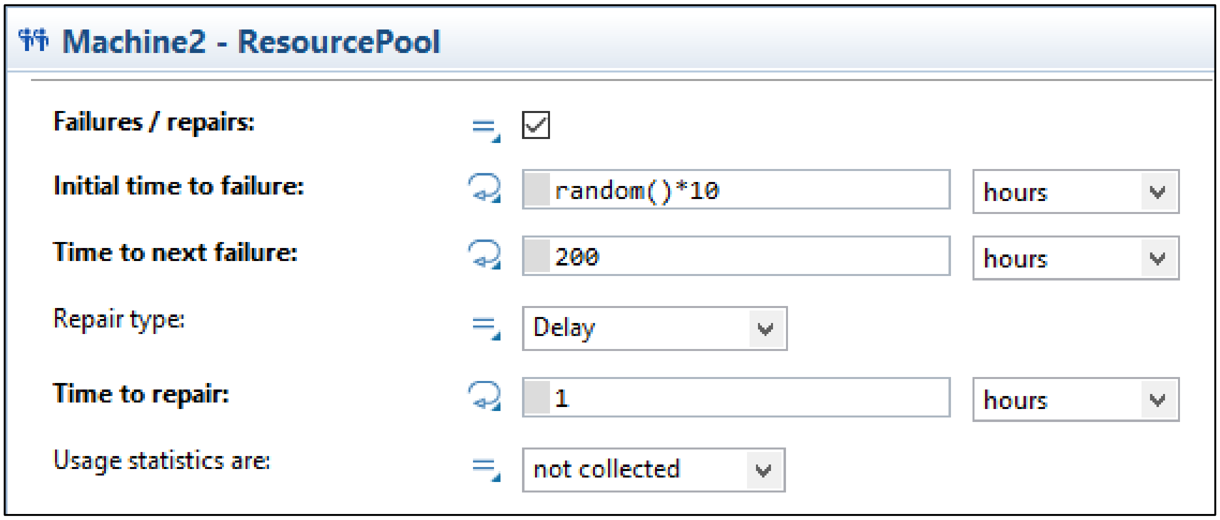

Figure 7. MTBF and MTTR information for the machines in AnyLogic

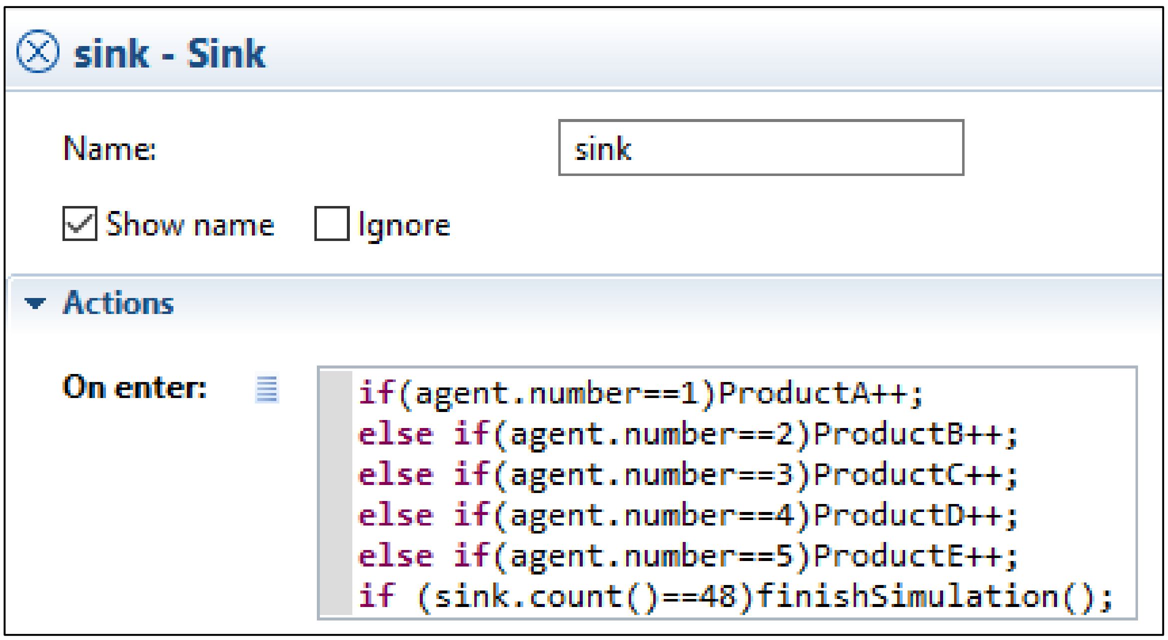

Figure 8. JAVA code to count finished parts based on product type

2.3 System Advisor Model

SAM is a performance and financial model simulation software designed to facilitate decision making for people involved in the renewable energy industry [30]. SAM uses libraries of performance data and coefficients that describe the characteristics of the system that is being modeled [30]. In this thesis, we are interested in obtaining the hourly power generated by the PV system and the wind turbines based on the capacity. Hence, we use the performance model that excludes the financial part when modelling the PV system and wind turbines. The hourly wind speed data and solar irradiance are assumed representative of Phoenix, AZ, USA. The different losses considered during modeling are provided in Table 1 [31].

Table 1. PV equipment losses considered during modeling

PV Subarrays	Pre-Inverter Derates	Mismatch	0.980
		Diodes and Connections	0.995
		DC wiring loss	0.980
		Tracking Error	1.000
		Nameplate	1.000
Array	Interconnection Derates	AC wiring losses	0.99
		Step-up transformer losses	1
Performance Adjustment	System Output Adjustments	Year-to-year decline in output (%)	0.5

2.4 AnyLogic Agent Based Model

In this section, we build a simulation model considering on-site RET consisting of PV panels, wind turbines and battery bank as shown in Figure 9.

The hourly demand of the manufacturing facility is met using the hybrid system under the TOU demand response program. The hourly energy data for PV system and wind turbine for various capacities is generated from the SAM. The PV-wind-battery system is built using an hourly time interval (Δt = 1hr) for a duration of 1 year.

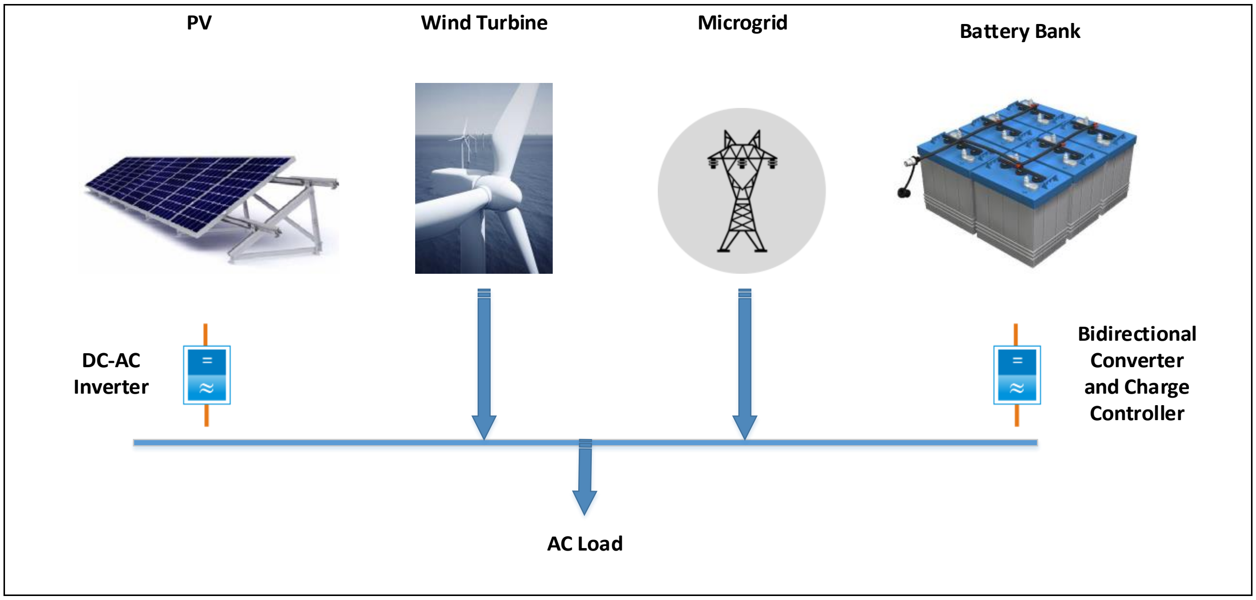

Figure 9. Renewable energy technology and battery bank integrated to the microgrid

2.4.1 TOU demand response program

A TOU demand response program is selected considering the availability of the renewable resources and utilization of the battery bank. A typical TOU pricing program is shown in Table 2 [32], it divides the day into on-peak and off-peak hours and the year into summer and winter wherein the electricity rates are higher during the on-peak hours. This information is used to design the dispatch strategy for the hybrid system. Parameters are defined based on the information provided in Table 2 and shown in Table 3.

Table 2. A typical time-of-use hours and pricing information

Season	Type	Time of Day	Electricity rate ($/kWh)	Demand Charge ($/kW)	Fixed Charge ($)
Summer (June – Sept)	Off-peak	7pm – 1pm	0.08274	0	51.42
	On-peak	1pm – 7pm	0.1679	18.8	
Winter (Oct – May)	Off-peak	9pm – 10am	0.08274	0	
	On-peak	10am – 9pm	0.11224	8.12	

Table 3. Parameters denoting the electricity rates

Rate	Unit	Cost
R_{W_OFP}	($/kWh)	0.08274
R_{W_ONP}	($/kWh)	0.11224
R_{S_OFP}	($/kWh)	0.08274
R_{S_ONP}	($/kWh)	0.1679
R_{spl}	($/kWh)	0.04
R_{W_DC}	($/kW)	8.12
R_{S_DC}	($/kW)	18.8

In AnyLogic simulation program, an agent based modeling approach is used to recreate the PV-wind-battery hybrid system environment. Statecharts are the main building blocks in the agent-based models. They are used to follow the TOU program and take actions corresponding to their current state. Figure 10 shows statecharts following the TOU program.

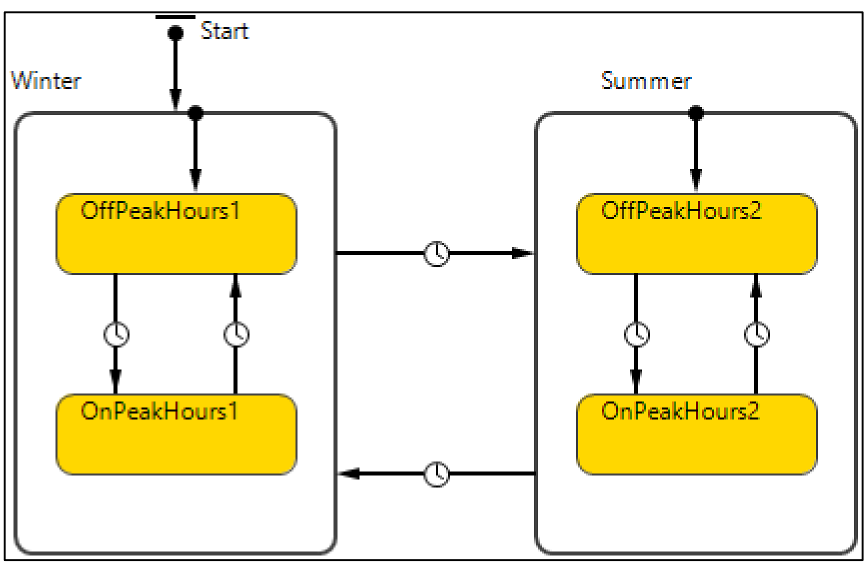

Figure 10. Statecharts used for modeling TOU hours in AnyLogic

The TOU hours i.e. Off-peak hours and On-peak hours represent the states of the statecharts. The transition from one state to another is triggered by a timeout function which occurs after a certain specified time. For example, during winter, the 'off-peak hours' state will transit to on-peak hours after a duration of 13 hours. Also, after a specified period the winter state also transits to the summer state. Whenever a new state is active, it triggers an event, which is a cyclic event recurring after every hour and executing the dispatch strategy of the hybrid system. The events, variables and the parameters are shown in Figure 11.

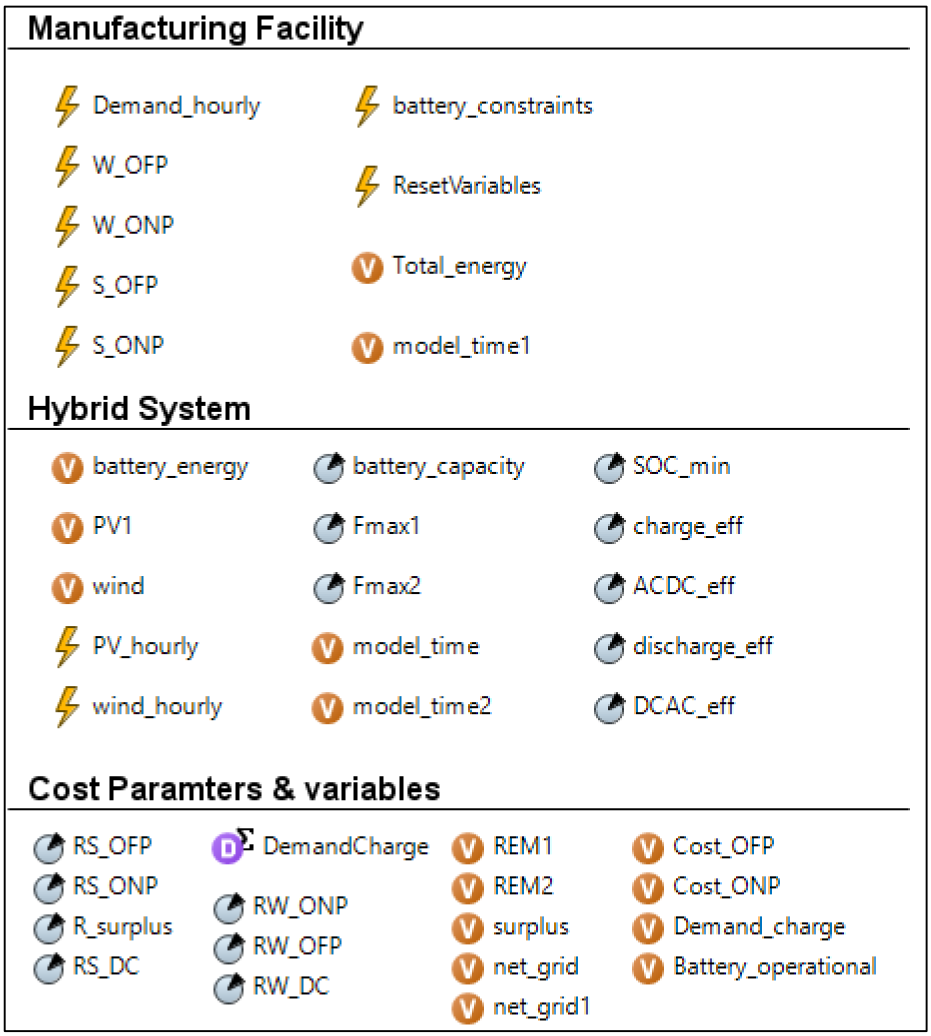

Figure 11. Parameters, variables, events, statistic objects used during modeling

The statistics object in AnyLogic calculates the statistical information on the series of data samples and this object is used to find the maximum demand within a month to calculate the demand charge.

Whenever the ‘on-peak hours’ state is active, the statistics object records the energy supplied by the grid. Figure 12 shows the statecharts that are used to calculate the demand charge.

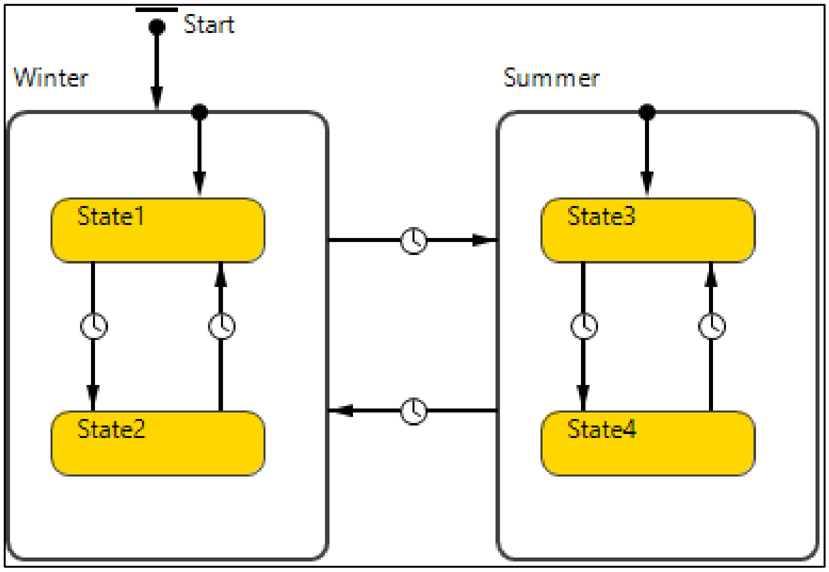

Figure 12. Statecharts used to calculate demand charge in AnyLogic

The transition from one state to another is triggered by a timeout after a period of one month. During the transition the demand charge for the previous month is calculated and recorded in a variable and the statistic object is reset for recording new data.

2.4.2 Dispatch Strategy

The dispatch strategy is based on meeting the demand and the battery bank state of charge (SOC) during the on-peak and off-peak hours. The system doesn’t differentiate between the energy obtained from different renewable energy technologies, hence the dispatch strategy remains the same irrespective of different RET. Since the discharge from the battery bank is limited during on-peak hours, the dispatch strategy follows in accordance with the TOU hours. The dispatch strategy for off-peak and on-peak hours are shown in Figure 13 and Figure 14 respectively.

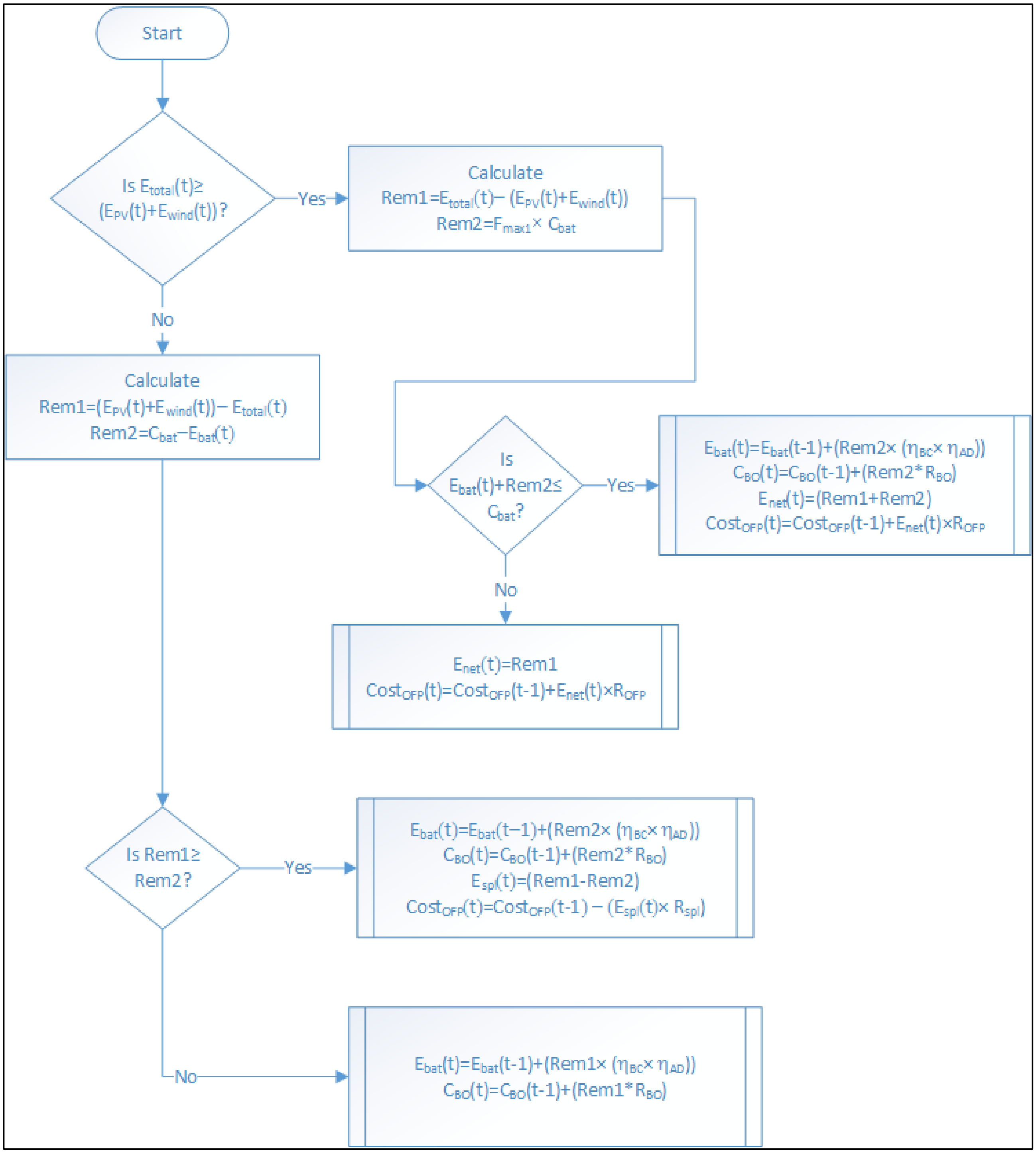

Figure 13. PV-wind-battery hybrid system dispatch strategy during Off-peak hours

During the off-peak hours, the energy from RET is supplied for all time ‘*t*’ to meet the load and deficit energy if any is taken from the grid. Battery bank is never discharged during this period; moreover, if the PV system is not enough to power the load and charge the battery bank, the grid is used to meet energy requirements. The battery can only be charged considering a specified maximum charging rate (F_{max1}) when using energy from the grid. Battery state of charge is checked before charging the battery, if the battery is full, surplus energy from the PV system is sold back to the grid. Battery operational cost is calculated when the battery is in a state of charge/discharge.

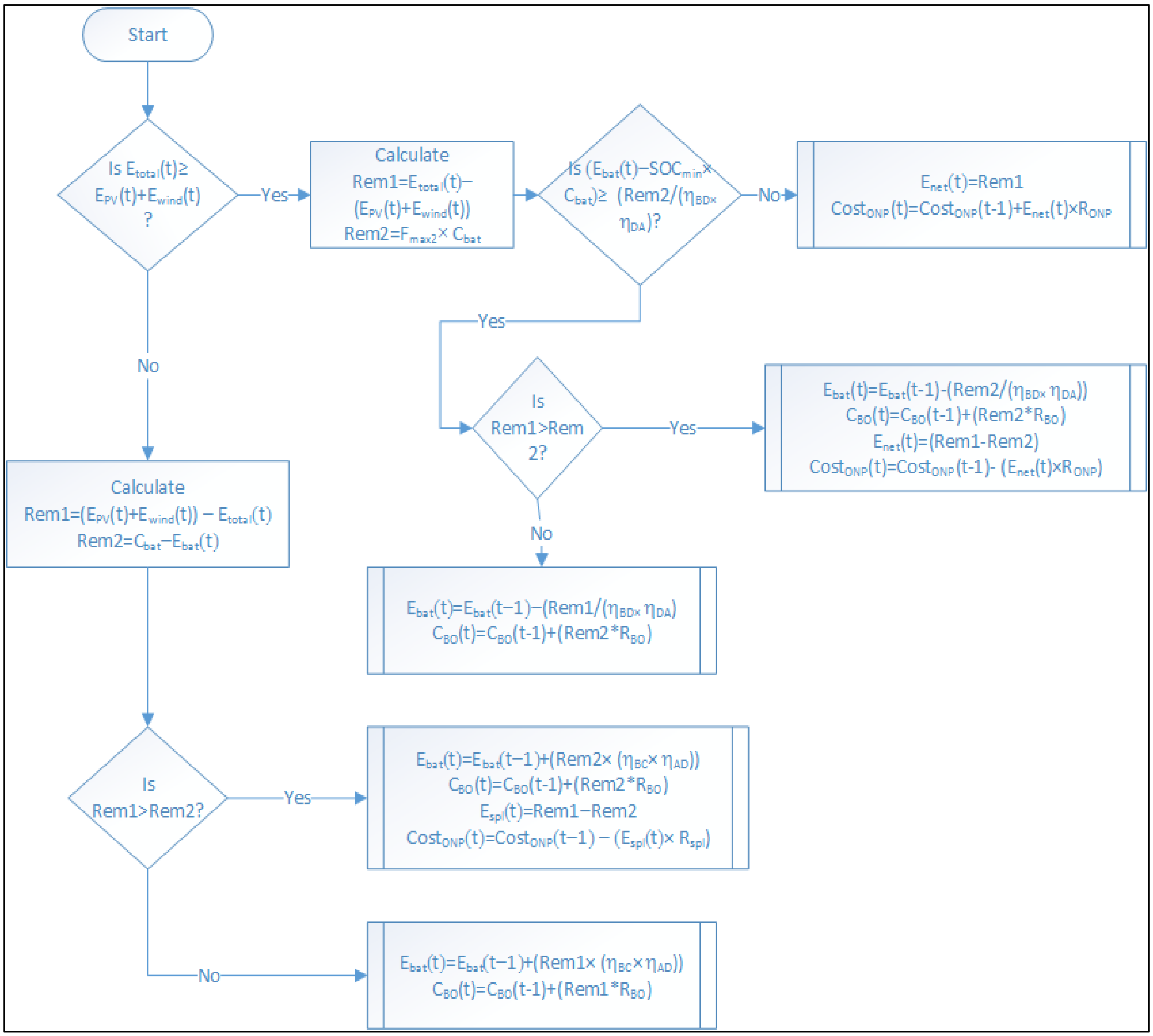

Figure 14. PV-wind-battery hybrid system dispatch strategy during On-peak hours

During the on-peak hours, the RET supply energy to meet the demand and excess energy if any is used to charge the battery bank depending on the SOC of the battery. Any surplus energy is sold back to the grid. If the power output from the RET is not enough to meet the load requirement, the battery bank is discharged based off of the maximum discharge rate (F_{max2}). The battery bank can only discharge until it reaches to its minimum state of charge (SOC_{min}). The grid is used to meet the load only when the hybrid system has supplied all of its power during that interval.

2.5 Simulation Based Optimization

In order to find the optimal solution for the product sequence and labor requirement using the discrete event model and the optimal battery storage using the agent-based model, a built-in simulation based optimization package called OptQuest is used. The OptQuest optimizer uses metaheuristics, mathematical optimization and neural network components based on the objective function, constraints, requirements, and parameters (decision variables) that can be varied [33]. Figure 15 shows the logic behind the OptQuest Optimizer [34].

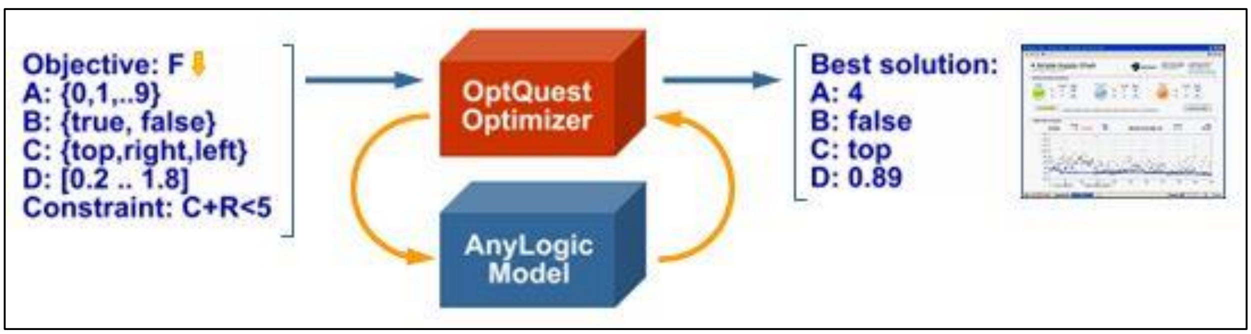

Figure 15. Logic behind the working of OptQuest optimizer

(Source: http://www.anylogic.com/experiment-framework)

Jain et al. [35] describes the OptQuest optimizer procedure to reach a global optimal solution. It applies three search heuristics to evaluate the problem which are scatter search, tabu search and neural networks.

2.5.1 Simulation Based Optimization for DES model

The objective of this experiment is to find the optimal product sequence and labor requirement. Before we set up the optimization experiment, select-Output object is added to differentiate agents according to their product type and the output links from the select-Output object are connected to delay blocks as shown in Figure 16.

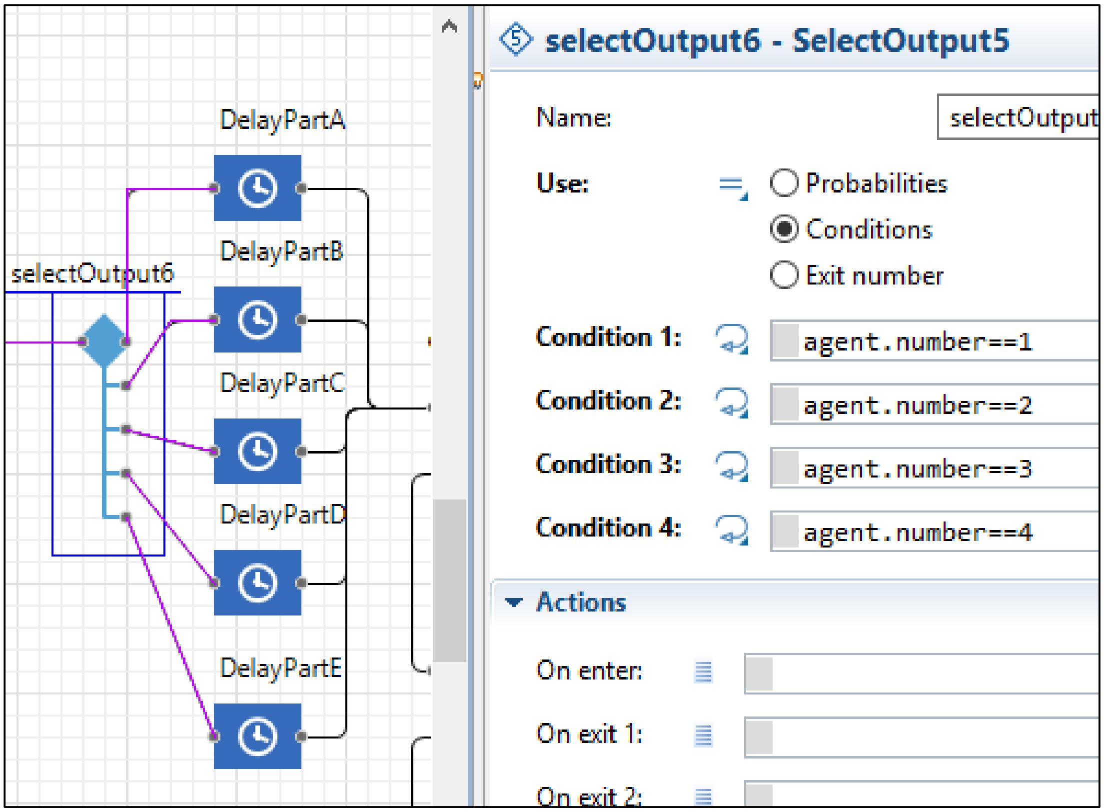

Figure 16. Select-Output object to differentiate parts and delay objects to prioritize parts

The objective function is defined by the expression shown in (1)

$$\min_{P1,P2,P3,P4,P5} (NOperators + NPainters) \tag{1}$$

Where *P1* through *P5* are discrete variables that take a value between zero and five and they represent the delay time in seconds. $NOperators$ and $NPainters$ are the parameters for the total number of operators and total number of painters. Furthermore, there is a throughput constraint for meeting the demand for each given product type.

2.5.2 Simulation Based Optimization for Agent Based Model

For each case, to find the optimal battery capacity, maximum charge rate (F_{max1}) and maximum discharge rate (F_{max2}), we run the optimization experiment using OptQuest. The objective function is formulated as shown in equation (2)

$$\min_{C_{bat}, F_{max1}, F_{max2}} (Cost_{OFP} + Cost_{ONP} + Cost_{DC} + C_{bat} \times R_{bat} \times CRF + Cost_{BO}) \qquad (2)$$

Where $Cost_{OFP}$ is the cost of electricity during the off-peak hours, $Cost_{ONP}$ is the cost of electricity during the on-peak hours, $Cost_{DC}$ is the cost incurred due to the demand charge, C_{bat} is the battery capacity and $Cost_{BO}$ is the battery operational cost. The decision variables for the objective function are battery bank capacity (C_{bat}, having lower bound 0 and upper bound 1000), F_{max1} and F_{max2} (having lower bound 0 and upper bound 1). R_{bat} is battery initial investment including replacement in ($/kWh) and CRF is capital recovery factor which is discussed later.

During the sampling intervals, the battery balance constraints [18] are given by (3) and (4)

$$E_{bat}(t) \geq C_{min} \times C_{bat} \qquad (3)$$

$$E_{bat}(t) \leq C_{bat} \qquad (4)$$

The available state of charge of the battery bank at time any time '*t*' should not fall below the minimum state of charge and cannot exceed the battery capacity.

2.5.3 Computing Annual Savings

The RET are expensive in terms of capital investment and usually take a long time to pay off the initial investment. In this thesis, it is assumed that the annual energy produced by the RET and the demand is constant over the lifetime of RET. Under this assumption, capital recovery factor (CRF) is used to uniformly distribute the investment cost of RET over the analysis period [36]. The total annual cost for each system is given by:

$$TAC = (Initial\ investment\ \times CRF) + O\&M\ cost \tag{5}$$

$$CRF = \frac{d \times (1+d)^A}{(1+d)^A - 1} \tag{6}$$

Where d is the discount rate and A is the analysis period. The project lifetime period is greater than the analysis period and the initial investment will be paid off during the analysis period. Later, the system only incurs the O&M cost of RET and electricity cost from the grid.

$$\begin{aligned} &Total\ cost\ for\ entire\ project \\ &\quad = \{(TAC_{PV} + TAC_{WIND} + TAC_{bat} + Cost\ from\ grid) \times A\} \\ &\quad + \{(O\&M\ cost + Cost\ from\ grid) \times (Project\ lifetime\ period - A)\} \end{aligned} \tag{7}$$

$$\begin{aligned} &Annual\ Savings \\ &= \frac{(Total\ cost\ considering\ the\ baseline\ scenario - Total\ cost\ for\ entire\ project)}{Project\ lifetime\ period} \end{aligned} \tag{8}$$

3 CASE STUDY

3.1 Paint Shop Manufacturing System

The paint shop consists of nine operating stations for processing parts of various product types. The process flow of the parts is shown in Figure 17. The cycle time of product types for different operations and labor requirements is provided in Table 4 and Table 5 respectively. The package size of the product indicates the number of parts processed at the same time. The weekly demand and package size of each product type is provided in Table 6. For each station, machine ratings and labor type are provided in Table 7. Furthermore, the transportation time for the parts from one station to another station is 10 min. Buffer size between the stations is one, hence, parts have to wait until the job at the succeeding station is completed. The Mean Time Between Failures (MTBF) and Mean Time To Repair (MTTR) of the machines is once a week and one hour respectively. Note that all the data except for the machine ratings is based off of real data from our industrial partner while machine ratings are assumed.

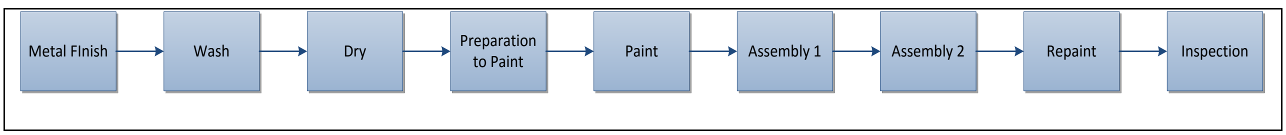

Figure 17. Process flow diagram for the parts of different product type

Table 4. Cycle time of five product types for different operations

Product Type	Metal Finish	Wash	Dry	Preparation to paint	Paint	Assembly 1	Assembly 2	Repaint	Inspection
Product A	0.83	1.25	1.625	2.03325	1.25	2.4534	1.5	2	1
Product B	0	0.5	0.92	1.4	0.78	0	0	1.03	0.87
Product C	0	1.15	0.93	1.415	0.83	0.95	0.73	0.77	1.02
Product D	0	0.5	0.77	1.98	0.67	0	0.87	0.8	1.5
Product E	0	0.38	0.7	1.15	0.9	2.2	0	0	0.5

Table 5. Labor required to process parts of different product types

Product Type	Metal Finish	Wash	Dry	Preparation to paint	Paint	Assembly 1	Assembly 2	Repaint	Inspection
Product A	1	1	2	4	1	5	2	1	1
Product B	0	1	1	2	1	0	0	1	1
Product C	0	1	1	2	1	1	1	1	1
Product D	0	1	1	1	1	0	1	1	1
Product E	0	1	1	1	1	1	0	0	1

Table 6. Weekly demand and package size for different product types

Product Type	Weekly Demand	Package size
Product A	12	2
Product B	9	1
Product C	18	2
Product D	22	1
Product E	24	12

Table 7. Rated power and labor type for each operation

Machine	Rated Power (kW)	Labor type
Metal Finish	22	Operators
Wash	18	Operators
Dry	19	Operators
Preparation to paint	15	Operators
Paint	22	Painters
Assembly 1	25	Operators
Assembly 2	23	Operators
Repaint	22	Painters
Inspection	12	Painters

3.1.1 Results from the Discrete Event Simulation Model

The optimization experiment returns the parameter values provided in Table 8. The delay times, $P1$ through $P5$ imply that Product A, Product D and Product E have higher priorities than Product B and Product C. Considering the default sequence and the result from the optimization experiment, the optimal product schedule is Product A – Product D – Product E – Product B – Product C. Using the parameters from the table, the makespan obtained is 96.59 hours while the makespan for the default sequence is 102.41 hours.

Table 8. Results from the Optimization experiment

Parameters	**Unit**	**Value**
$P1$	Sec	2
$P2$	Sec	5
$P3$	Sec	5
$P4$	Sec	2
$P5$	Sec	2
$NOperators$	-	15
$NPainters$	-	3

This case study considers a paint shop manufacturing system for determining the optimal product sequence and labor assignment. We propose a DES model that incorporates the cycle time and labor required for each product by creating a custom agent and defining its attributes. An optimization experiment with OptQuest is developed to obtain a near optimal solution. The results of the case study show that a 5.68% decrease in the makespan time is achieved while determining labor requirement.

3.2 Case Study with Renewable Energy Technology

The objective of this case is to minimize the electricity cost incurred from the grid by determining the capacities of the DG units. The manufacturing facility is in operation from 6 AM – 7 PM, for seven days a week. The demand is assumed constant every week. The hourly demand for the entire week is shown in Figure 18.

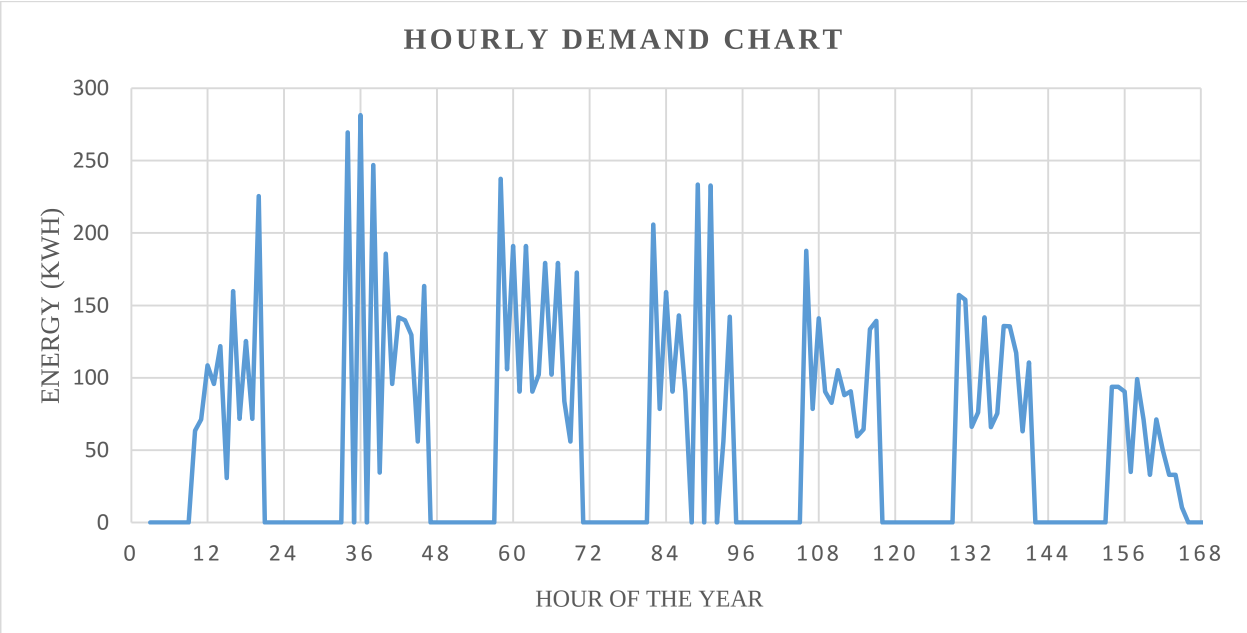

Figure 18. Hourly demand for one week

The financial parameters are provided in Table 9 and the cost parameters for the PV and wind turbine are shown in Table 10 and

Table 11 respectively [35]. The technical and economical parameters of the battery bank are provided in Table 12 [35].

Table 9. Financial Parameters

Financial Parameter	**Unit**	**Value**
Discount rate	%	5

Analysis period	Years	20

Table 10. Economic data for the photovoltaic system

Photovoltaic parameters	**Unit**	**Value**
Module cost	($/kW)	2050
Inverter cost	($/kW)	370
Operation & Maintenance costs	(% Initial investment/year)	1
Lifetime period	Years	25

Table 11. Economic data for the Wind turbines

Wind turbine parameters	**Unit**	**Value**
Initial investment	($/kW)	3103
Operation & Maintenance costs	(% Initial investment/year)	3

Table 12. Technical and economic parameters for the battery bank

Battery bank parameters	**Unit**	**Value**
Minimum state of charge (C_{min})	%	30
Discharge efficiency of the battery (η_{BD})	%	100
Charge efficiency of the battery (η_{BC})	%	80
AC-DC conversion efficiency of the invertor (η_{AD})	%	93.4
DC-AC conversion efficiency of the invertor (η_{DA})	%	93.4
Initial Investment	($/kWh)	200
Replacement cost	% of Initial Investment	80

Replacement period	Years	10

3.2.1 Baseline Scenario

We run the simulation considering the TOU program without the RET and battery storage to set a baseline for our analysis while considering the hybrid system. Table 13 shows the costs for the baseline scenario obtained from the simulation results.

Table 13. Cost incurred from the grid for the baseline scenario

Hour type	Cost ($)
Off Peak hours	15,489.55
On Peak hours	37,663.32
Demand charge	33,838.80
Total cost from grid in 1 year	86,991.67

3.3 Case Study 1

In this case study, we use a PV system along with battery storage in the agent based model. For different capacities of PV, the battery bank storage along with maximum charge and discharge rate is optimized using OptQuest as discussed in the earlier section. Figure 19 shows the annual savings for the different capacities of PV and the corresponding battery storage for each PV-battery hybrid system. The plot illustrate that the annual savings increase as the PV system capacity increases until it reaches maximum annual savings and then decreases for higher capacities of PV system as the system utilization decreases. The tradeoff is achieved at a capacity of 400 kW which implies any increase in capacity results into a loss. It is evident from Figure 19 that the maximum annual savings occur for the PV of capacity 200 kW with a battery storage of 288 kWh. Detailed cost analysis for obtaining the annual savings is shown in Table 14.

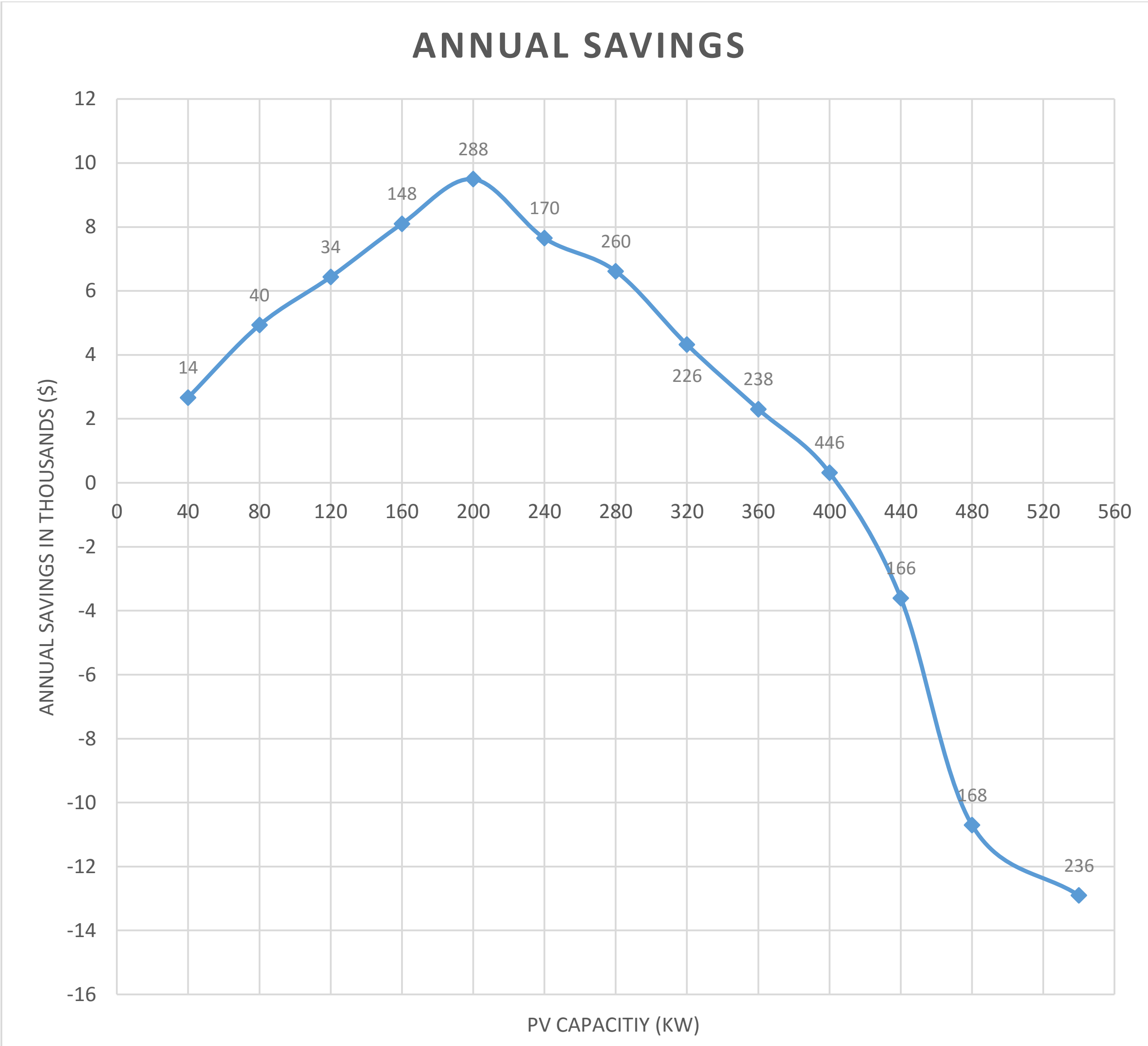

Figure 19. Annual savings for PV-battery hybrid system

Table 14. Detailed cost analysis for the PV-battery hybrid system

Cost Components	**PV-battery hybrid system**	**No hybrid system**
Cost from the grid in one year ($)	35,537.29823	86,991.67
PV initial investment (module and inverter capital cost) ($)	475,816.90	-
PV O&M cost in one years ($)	4,758.17	-
Battery bank initial investment ($)	57,600.00	-
Battery bank replacement cost ($)	46,080.00	-
Total lifetime cost i.e. 25 years ($)	1,937,393.291	2,174,791.625
Estimated annual savings ($)	9,495.933	
Estimated annual savings (%)	10.915	

Figure 20 shows the monthly generation of the PV system, the net energy from the grid, the total battery bank discharge, and the charge energy for the PV-battery hybrid system with maximum annual savings. Although the electricity rate during the on-peak hours is high, actual cost incurred from the grid is lower as compared to the cost during off-peak hours due to discharge of energy from the battery bank. Another interesting observation is that the net energy from the grid during the summer is very low; however, cost during on-peak hours in the summer is high as compared to the rest of the year regardless of high energy generation from the PV system. Moreover, the battery discharge energy is lower during summer as compared to winter and thus more energy is sold to the grid as surplus rather charging the battery bank.

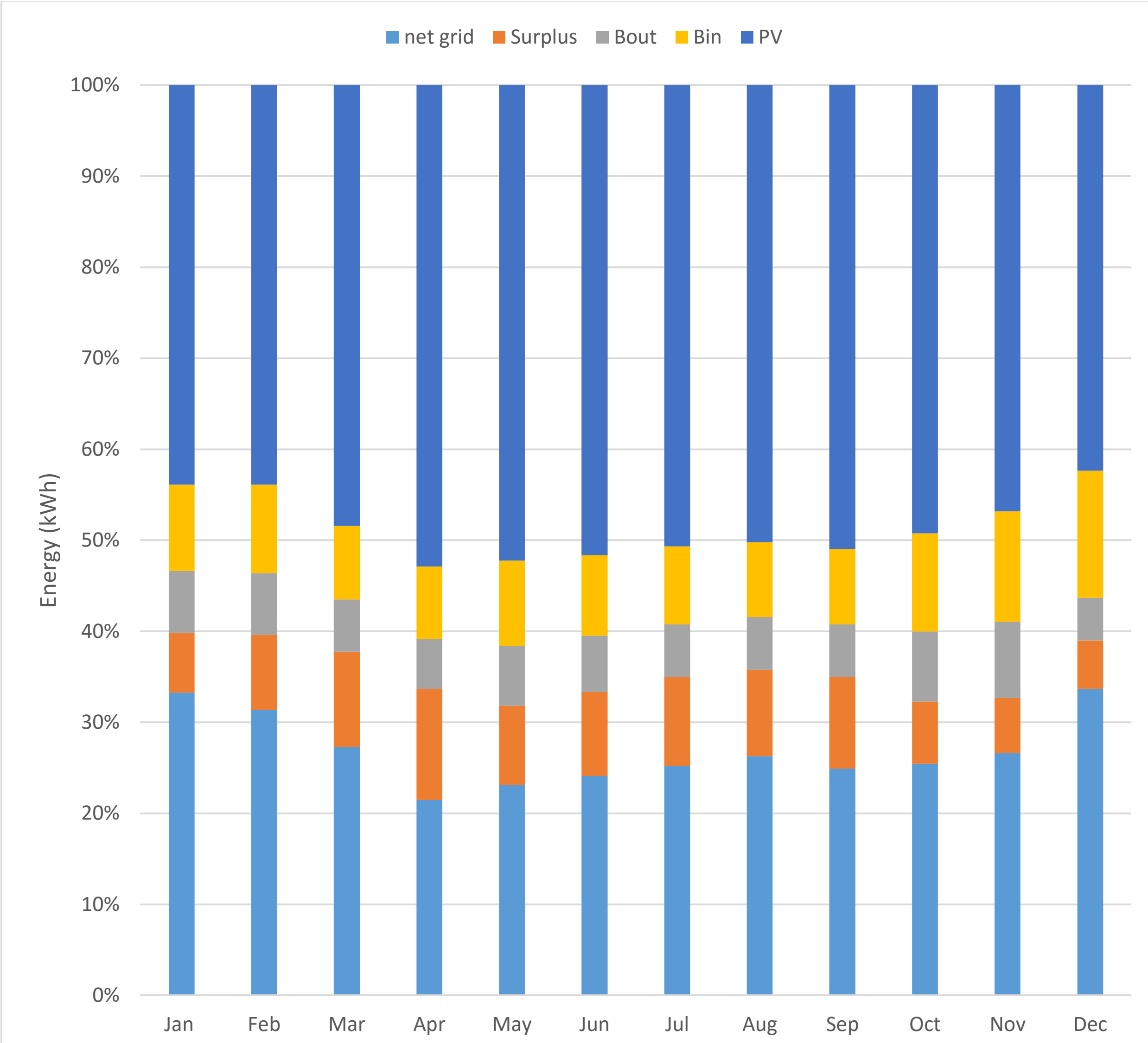

Figure 20. Monthly energy generation from PV, charge and discharge energy from the battery bank, energy supplied by the grid and surplus energy sold back to grid for PV-battery hybrid system

Figure 21 shows the hourly energy consumption from each subsystem needed to meet the demand. It is evident from the Figure 21 that RET (PV system) is sufficient to meet the total demand. The high correlation between the global horizontal irradiance and demand helps to lower the cost of electricity during the on-peak hours. Battery bank is discharged to assist the RET or discharged completely in order to meet demand and lower the demand charge during the on-peak hours. Moreover, the net energy taken from the grid during on peak hours is much less which leads to significant cost savings. It is also interesting to observe the energy utilized to charge the battery bank which can be seen for the points that exceed the demand.

Figure 22 shows hourly energy generated from the PV system, surplus, battery input and output energy and its state of charge (secondary y-axis) for a week in February. The PV system is the major contributor to charge the battery bank as seen from the SOC plot. When the battery bank is completely charged and demand is met, the excess solar energy is sold to the grid as surplus. Although the objective is to better utilize the solar energy for meeting the load requirement and charging the battery bank, thereby, avoiding excess energy sold to the grid.

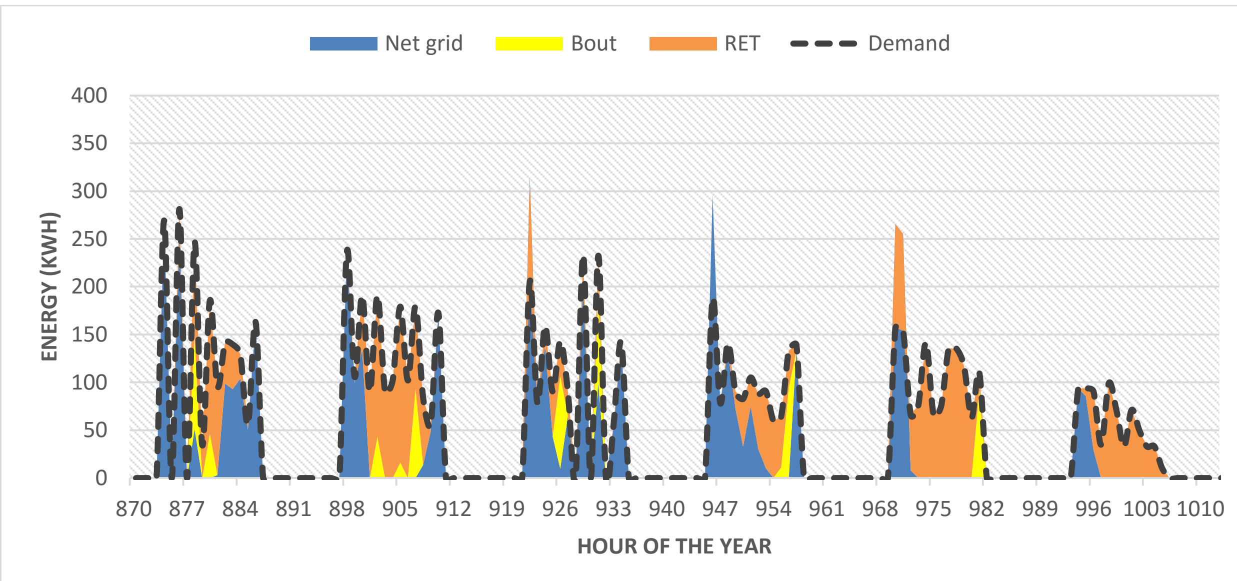

Figure 21. Hourly consumption energy profile of each subsystem to meet demand for PV-battery hybrid system

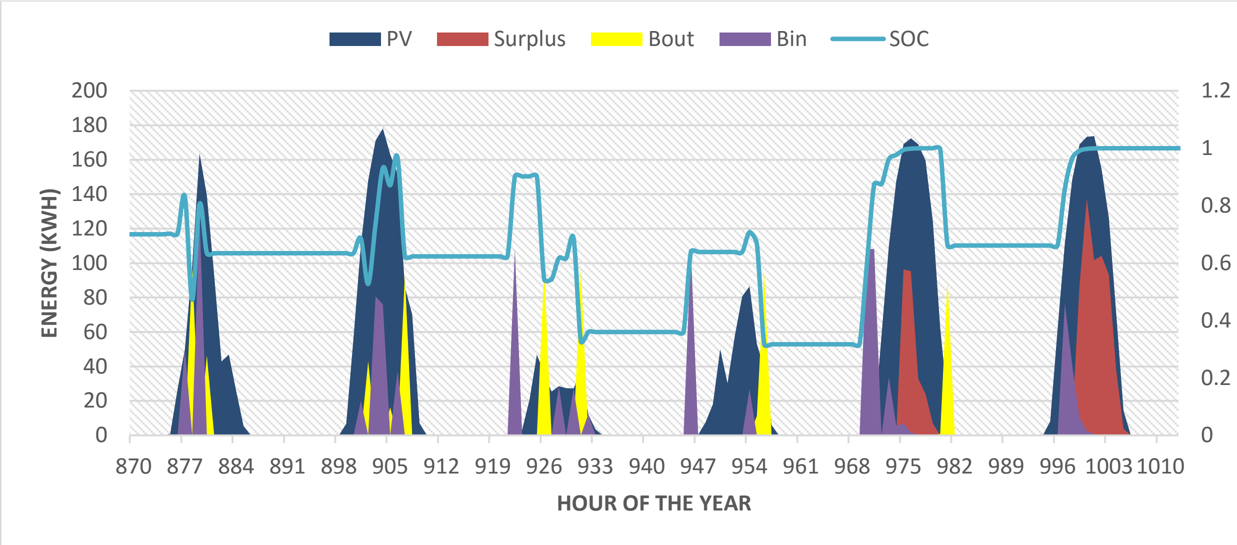

Figure 22. Hourly energy generated from PV system, surplus, battery input and output energy and its state of charge (secondary y-axis)

3.4 Case study 2

In this case study, we introduce wind turbines to our existing model with PV and battery storage. Since the wind turbines can generate electricity during the period when manufacturing is off, it can be used to charge the battery bank and avoid any associated cost incurred from the grid. In addition, the wind turbines can also assist the PV system to supply energy to meet the demand. Figure 23 shows the annual savings for the different capacities of PV and wind turbines and corresponding battery bank capacity for the given capacity of PV and wind turbine. The capacities of the PV system remain same from the previous case, while wind turbine capacities varied for 30, 50, and 70 kW. The annual savings plot indicates the annual savings for the wind turbine with a capacity 30kW and 50kW shows a similar pattern while the plot for wind turbine capacity 70 kW show lower annual savings. For a PV capacity of 160 kW, wind turbine farm size 30 kW and battery bank storage of 290 kWh, we obtain the maximum annual savings of $7720.51. Also, notice that overall capacities for the PV and battery storage are reduced with the addition of wind turbines. The tradeoff for the wind turbines with capacity 30 kW and 50 kW is achieved at 360 kW PV system capacity while the tradeoff for wind turbine 70 kW is achieved for PV system capacity higher than 280 kW. Detailed cost analysis for obtaining the annual savings is shown in Table 15.

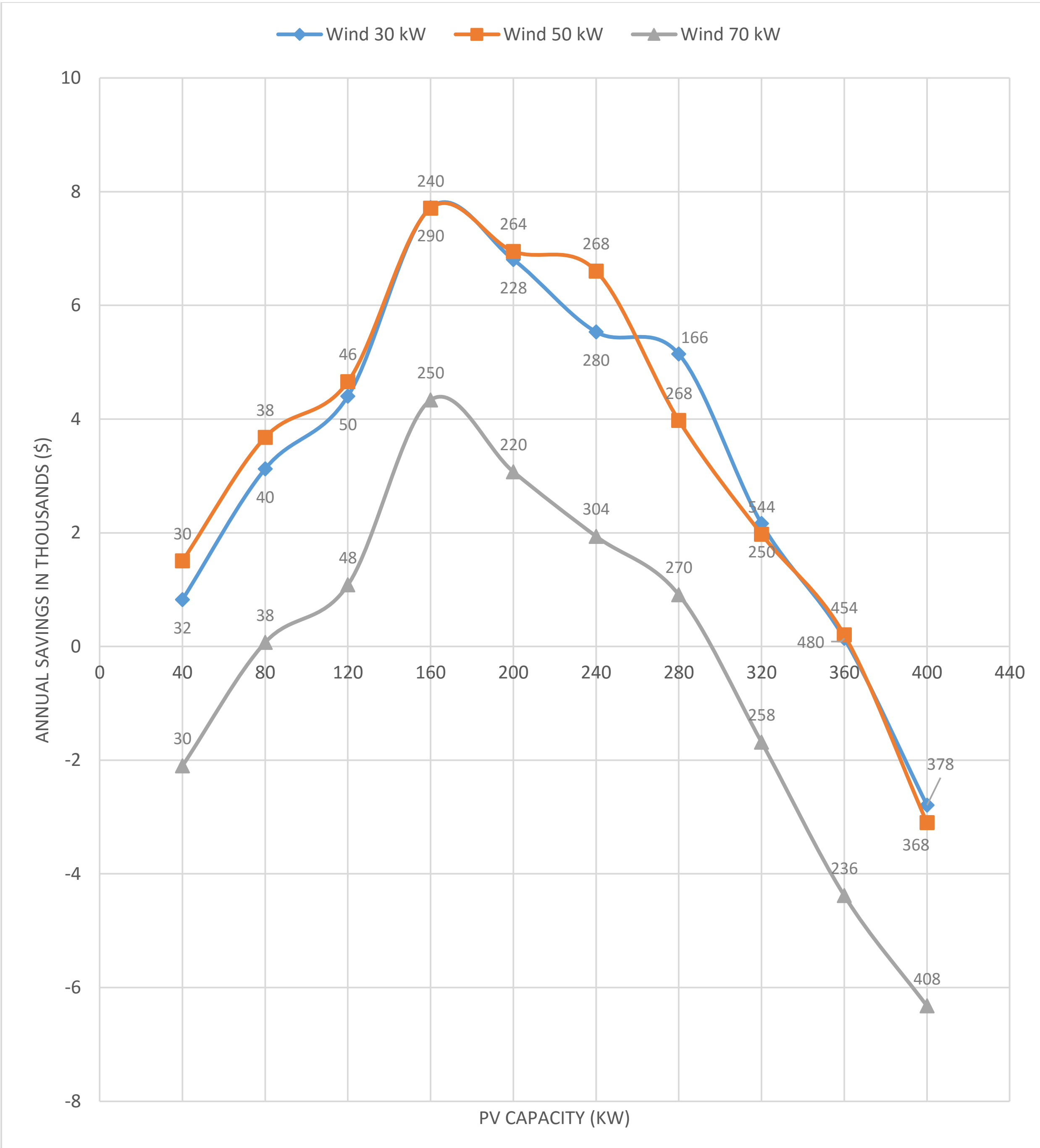

Figure 23. Annual savings for different capacities of PV and wind turbines for PV-wind-battery hybrid system

Table 15. Detailed cost analysis for the optimal PV-Wind-battery hybrid system

Cost Components	**PV-wind-battery hybrid system**	**No hybrid system**
Cost from the grid in one year ($)	38,904.053	86,991.665
PV initial investment (module and inverter capital cost) ($)	379,902.40	-
PV O&M cost in one years ($)	3,799.024	-
Wind turbine initial investment ($)	58,164.3	-
Wind turbine O&M cost in twenty years ($)	1,744.929	-
Battery bank initial investment ($)	58,000	-
Battery bank replacement cost ($)	46,400	-
Total lifetime cost i.e. 25 years ($)	1,981,778.791	2,174,791.625
Estimated annual savings ($)	7,720.51	
Estimated annual savings (%)	8.87	

The monthly production from the PV-wind-battery hybrid system and net energy from the grid is shown in Figure 24. Power generated by the wind turbines is low during summer while PV has maximum power generated during the summer, thus, the net energy supplied by the grid remains average. Due to a lower capacity of PV, the demand charges in the months of April and May are higher as compared to PV-battery case; however, the installed capacity is justified when considering the annual savings.

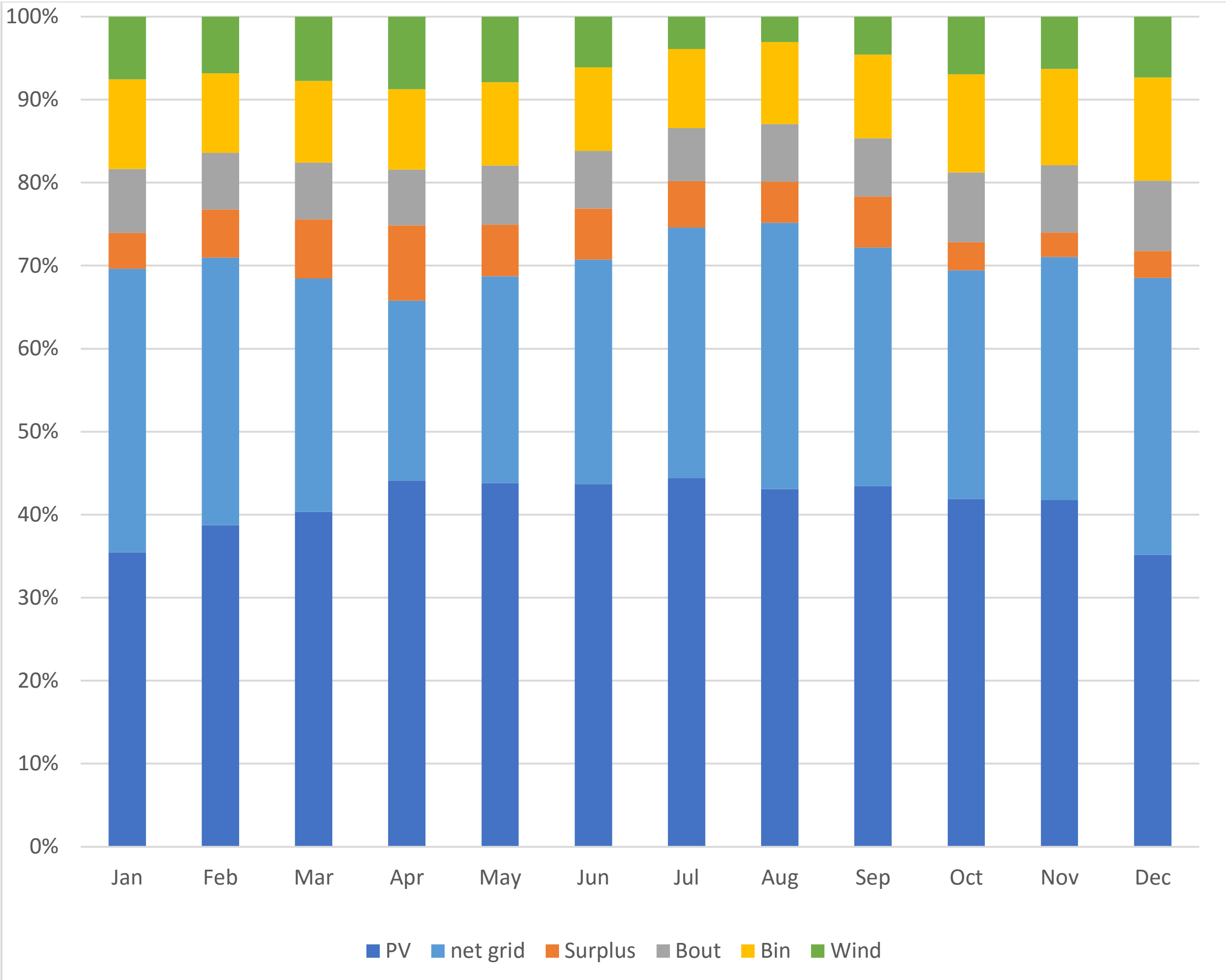

Figure 24. Monthly energy generation from PV, charge and discharge energy from the battery bank, energy supplied by the grid and surplus energy sold back to grid for PV-Wind-battery hybrid system

Figure 25 shows the hourly energy consumption profile for each subsystem to meet demand for PV-wind-battery hybrid system. Figure 26 shows the hourly energy generated by RET, surplus, battery input and output energy and its state of charge (secondary y-axis) for a week in February. The battery bank's objective is to balance the energy generated by the PV and wind turbines by utilizing it to supply energy during the on-peak hours to lower the demand charge. The wind turbines assist the PV to meet the demand, although, its main objective is to charge the battery bank when the manufacturing is off. The wind turbines play a significant role to charge the battery bank during the off peak hours and battery bank discharges to lower energy incurred from the grid during the on-peak hours.

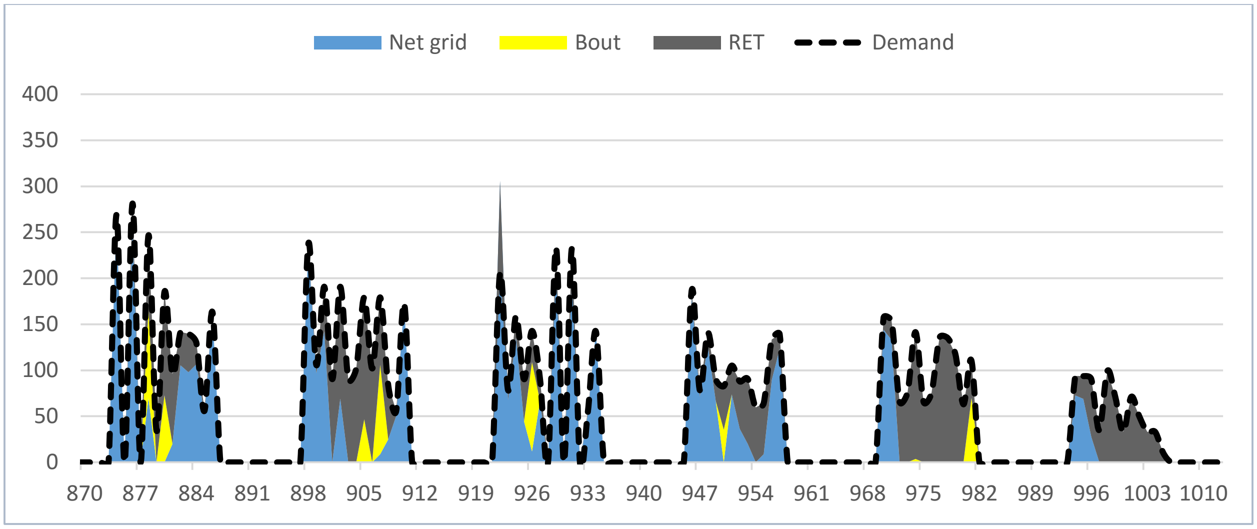

Figure 25. Hourly consumption energy profile for each subsystem to meet demand for PV-wind-battery hybrid system

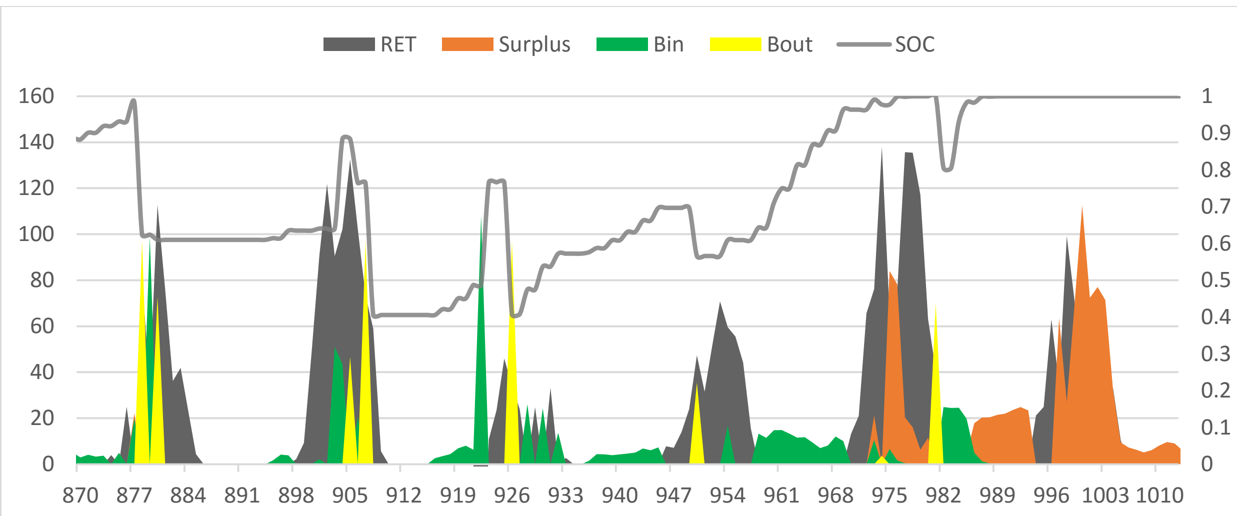

Figure 26. Hourly energy generated by RET, surplus, battery input and output energy and its state of charge (secondary y-axis)

3.5 Summary

Cost comparison for the different scenarios is summarized in Table 16. It is seen that the scenario with renewable energy technologies yield reduced cost considering its capital investment. Cost obtained from Scenario 2 and Scenario 3 are almost same with Scenario 2; nevertheless Scenario 2 outperforms Scenario 3 by $1,774.79 per annum.

Table 16. Cost comparison for the proposed and baseline scenario

Cost parameters	**Baseline (Scenario 1)**	**PV-battery hybrid system (Scenario 2)**	**PV-wind-battery hybrid system (Scenario 3)**
Cost from the grid in one year	86,991.67	35,537.29	38,904.05
Total lifetime cost i.e. 25 years ($)	2,174,791.625	1,937,393.29	1,981,778.79
Estimated annual savings ($)	-	9,495.93	7,720.51
% annual savings compared to baseline	-	10.91	8.87

4 SENSITIVITY ANALYSIS

A brief sensitivity analysis is conducted to account for variations in the weather conditions and equipment cost, and determine the impact if these factors on the system's annual savings. To evaluate the impact of weather conditions on the system, Global Horizontal Irradiance (GHI) and wind speed are varied for different combinations and corresponding annual savings are obtained. Sensitivity analysis is carried out for the optimal capacities for both the configuration i.e. PV-battery hybrid system and PV-wind-battery hybrid system.

4.1 Weather conditions

The weather conditions are varied for six different scenarios: (1) 10% increase and decrease in GHI; (2) 20% increase and decrease in GHI; (3) 10% increase and decrease in wind speed; (4) 20% increase and decrease in wind speed; (5) 10% increase and decrease in GHI and wind speed; (6) 20% increase and decrease in GHI and wind speed. The six scenarios are plotted against percentage increase and decrease in the annual savings from its original value. Figure 27 represents variations in percentage annual savings for change in weather conditions for the PV-battery hybrid system and Figure 28 represents variations in percentage of annual savings from the different weather conditions for the PV-wind-battery hybrid system.

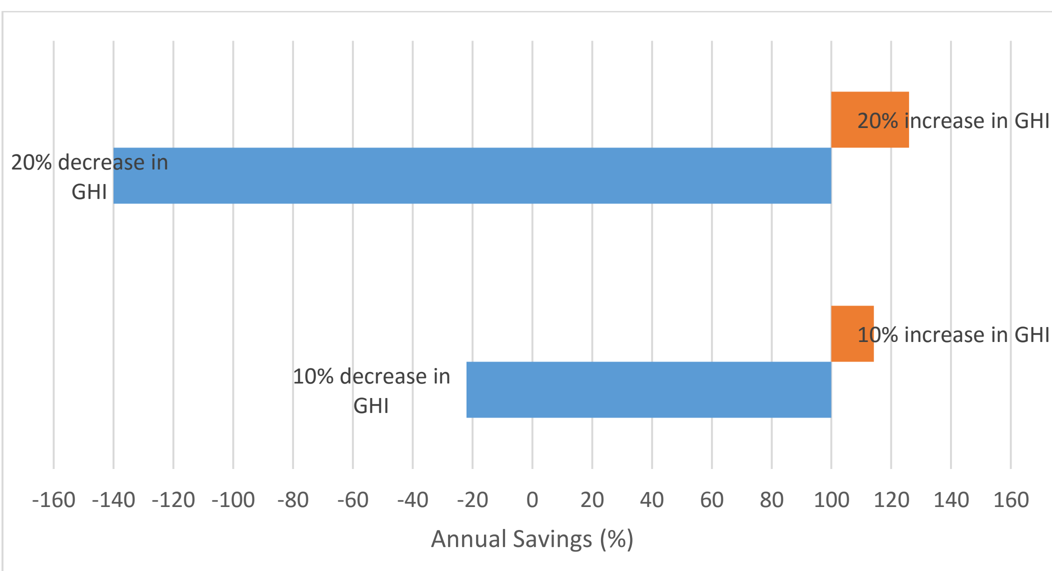

Figure 27. Variations in percent annual savings for weather data for PV-battery hybrid system

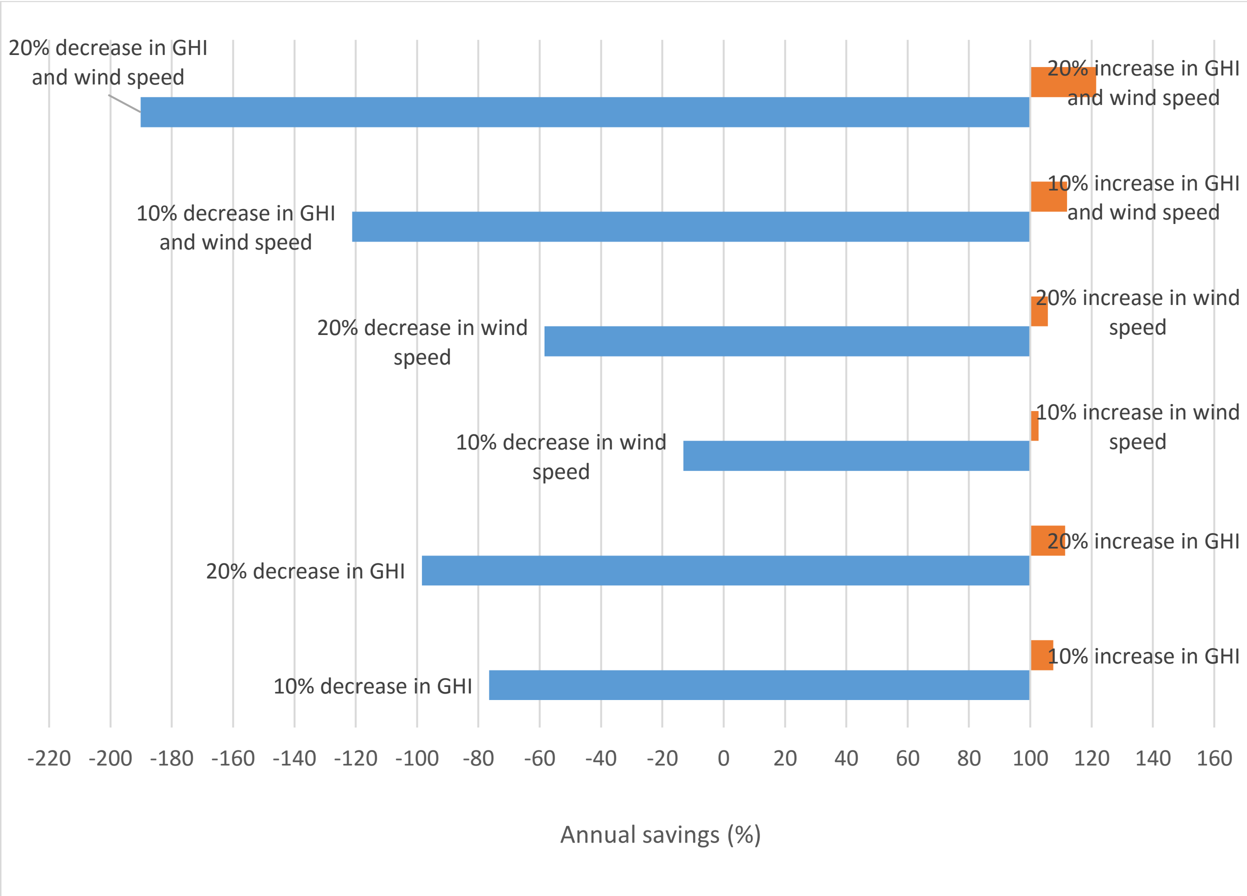

Figure 28. Variations in percent annual savings for weather data for PV-Wind-battery hybrid system

The plots show a significant reduction in the annual savings when decreasing the GHI or wind speed or both. This is due to the cost incurred from the demand charge (this is discussed later in detail). There is no significant increase found in the annual savings for the increase in GHI or wind speed or both. This trend is seen for both system configurations. Furthermore, the impact of varying GHI on the annual savings is more significant than varying the wind speed. Figure 29 and Figure 30 shows the comparison of demand charge incurred when there is no decrease in GHI or wind speed and when there is a 20% decrease in GHI or wind speed for both system configurations. It is evident from the plots that due to decrease in GHI or wind speed, the renewable energy technologies are incapable of generating enough power during the on-peak hours in the summer. Hence, the demand charge incurred from the grid is the main factor leading to a significant decrease in the annual savings. Moreover, the impact of decreasing the GHI on the annual savings is more significant for PV-battery hybrid system. Since, the OptQuest optimizer does not account for the variation in weather conditions, it is reasonable to choose higher capacities of PV and wind turbines.

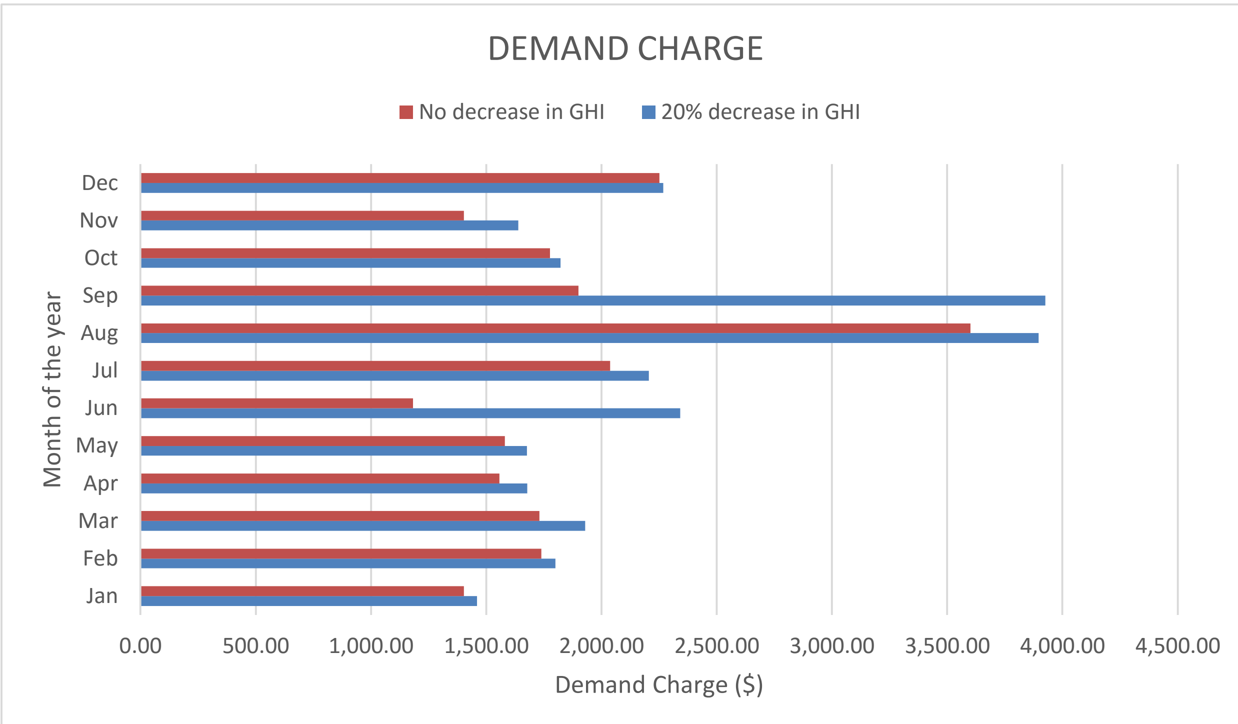

Figure 29. Demand Charge for percent change in GHI for PV-battery hybrid system

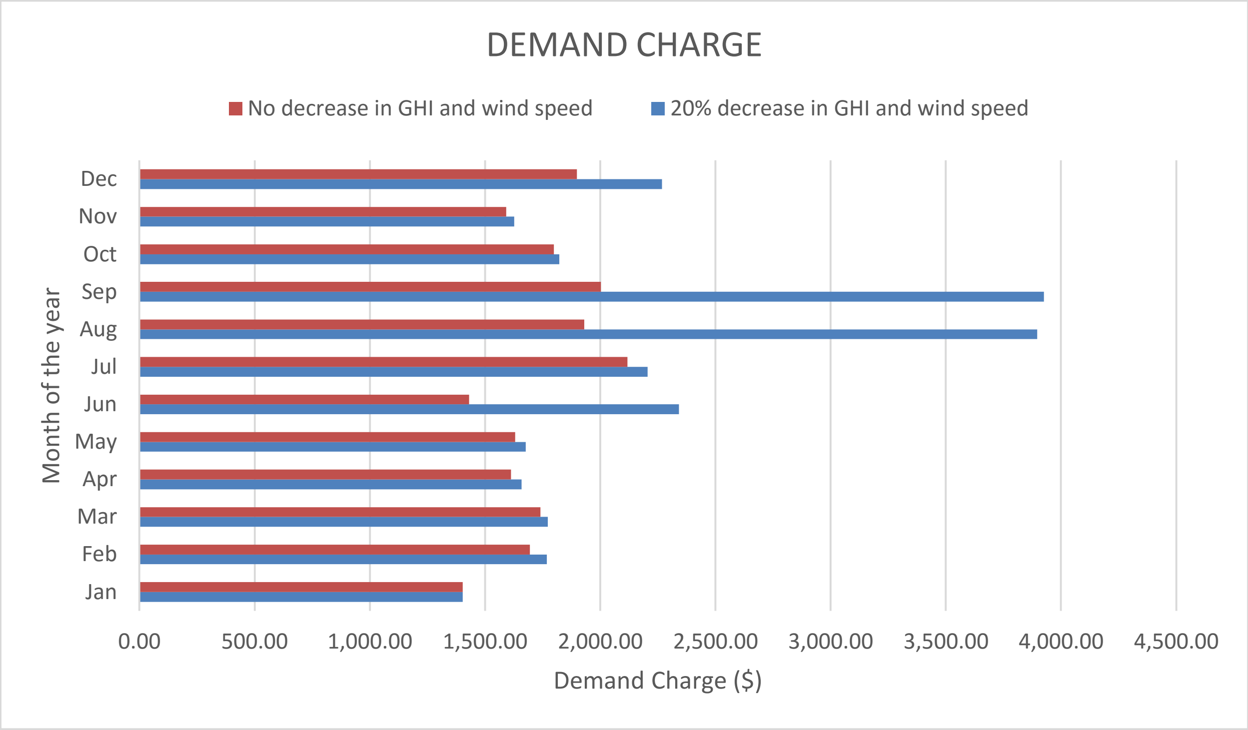

Figure 30. Demand Charge for percent change in GHI and wind speed for PV-Wind-battery hybrid system

4.2 Economic Data

To evaluate the impact of the system cost on the annual savings, the cost of the PV system, wind turbines and battery bank are varied one at a time by ±30 percentage from its original value. Figure 31 and Figure 32 shows the percentage annual savings for each system cost increased by 30% and decreased by 30% respectively for PV-battery hybrid system and PV-wind-battery hybrid system. It is evident from the plots that the annual savings are most affected by the PV system cost. Although, the wind turbines are expensive, its effect on the annual savings is the least significant of the three.

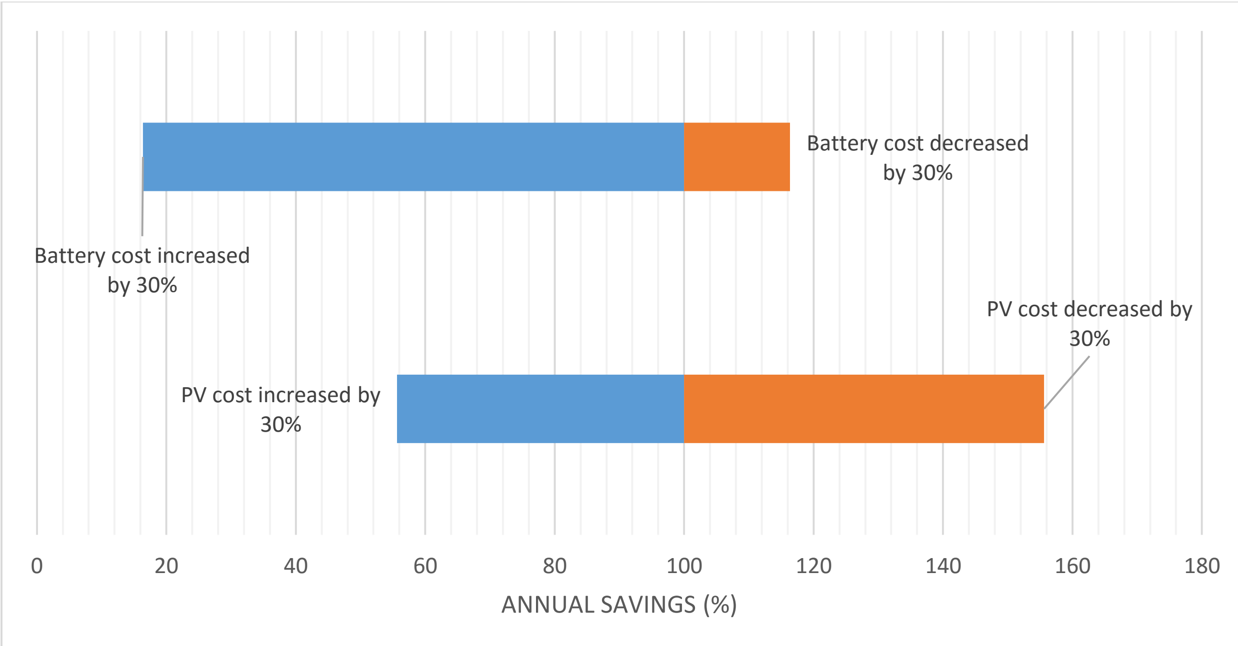

Figure 31. Sensitivity analysis on economic data for PV-battery hybrid system

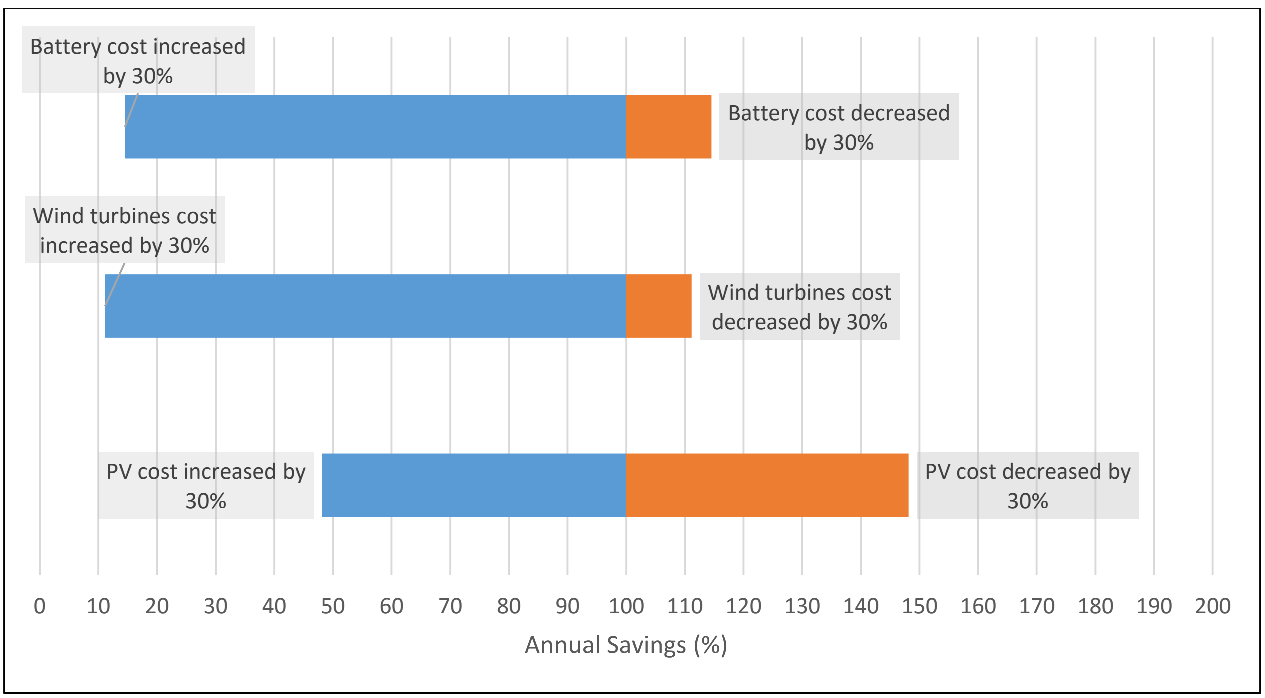

Figure 32. Sensitivity analysis on economic data for PV-Wind-battery hybrid system

5 CONCLUSION AND FUTURE WORK

This thesis presents a simulation based approach for sustainable manufacturing systems considering product sequence, labor assignment, and renewable DG system under a TOU demand response program. A DES model is developed by creating a custom agent having attributes that incorporate the information from the database into the model. A performance model in SAM is used to obtain hourly energy generated from the RET. An agent based model is developed to contain TOU statecharts, dispatch strategies, and to calculate the associated cost incurred from the grid. SBO using OptQuest is used to determine the product sequence, labor requirements, battery bank storage, and maximum charge/discharge rate.

A case study considering a paint shop manufacturing system is considered. For the DES model, optimal product sequence and labor assignment are determined under the constraints of production throughput and a 5.68% reduction in makespan is achieved. The DES model and SAM model are integrated to the agent based simulation model. Two scenarios considering PV-battery hybrid system and PV-wind-battery hybrid system is compared to the baseline scenario and a cost reduction of 10.91% and 8.87% is obtained respectively. The first case illustrates higher annual savings due to a large correlation between the demand and the GHI that justifies the large capacity of PV system. The second case illustrates that with the introduction of wind turbines, the capacities of the PV system and battery storage are reduced. Although the battery bank is charged using energy supplied by wind turbines, which reduces the cost during off-peak hours, the wind turbine’s capital investment and lower system utilization outweighs the overall cost benefit resulting into lower annual savings.

A sensitivity analysis is conducted considering variable weather and economic data. A significant variation in the annual savings is found while decreasing the GHI and wind speed due to an increase in the demand charge. Hence, it is recommended to choose higher capacities of RET than the capacities obtained from the annual savings plot. In addition to the risk associated with variation in weather conditions and system cost, the manufacturer must also consider the disadvantages of financing the capital investment, discount rate, and inflation.

The simulation model developed in this thesis represents an initial study. The simulation approach is extremely time consuming which is unattractive to manufacturers and it can only provide a good solution. Thus, in the future, this study can be used as a guide to develop an analytical model that can determine the optimal renewable energy capacity.

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